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Abstract

Separate identification of the price and quantity of human capital has important implications for understanding key issues in labor economics and macroeconomics. Price and quantity series are derived and subjected to robustness checks. The human capital price series associated with different education levels are highly correlated and exhibit a strong secular trend. Three resulting implications are explored: (1) using the derived quantities life-cycle profiles are re-examined; (2) the rising college premium is reinterpreted and found to be mainly driven by relative quantity changes, and (3) adjusting the labor input for quality increases dramatically reduces the contribution of MFP to growth.

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1 Introduction

The flow from human capital is by far the most important input in the world economy. The estimated share of labor in the U.S. and most of the OECD countries, for example, is about two thirds. There is quite general agreement that human capital plays a significant role in the determination of living standards. Human capital theory has been the basis of a huge literature studying the determination of earnings and inequality.[1] The recent rise in the skill premium and inequality in the U.S. has stimulated a large literature, based on the human capital framework, to provide an explanation.[2] At the same time, it has exposed a continuing weakness of human capital theory due to an inherent under-identification problem. This is a problem for many standard microeconomic based analysis of earnings patterns, but it is also a problem for macroeconomic growth studies. Payments to human capital may be directly observed, but a payment is a product of a price and a quantity. In general, neither the quantity nor the price of human capital is directly observable. Thus, when payment (wage) differences are observed between any observable groups, say by education level or by country, in general it is not possible to distinguish between whether the difference is due to a difference in prices or a difference in quantities, or some combination of the two. This has important implications for our understanding of many key issues in labor economics and macroeconomics, including the rising college premium, rising inequality, sources of growth and life-cycle productivity profiles. With a small number of exceptions, the vast literature on human capital has ignored this identification problem.[3] In most cases implicit identification assumptions are made, which we argue in this paper are generally not justified and usually represent one of two extremes: either constant quantities or constant prices over time.

Assessing the contribution of human capital to output, living standards and growth is hampered by serious conceptual and measurement problems due to this identification issue. It is well recognized that the quantity of the labor input cannot simply be measured by total hours.[4] An example of the

[1] Seminal works include Becker (1964), Ben-Porath (1967), and Mincer (1974).

[2] See, for example, Katz and Murphy (1992), Card and Lemieux (2001), and the survey by Katz and Autor (1999), for traditional labor economics approaches, and Krusell *et al.*(2000), Guvenen and Kuruscu (2007) and Huggett, Ventura and Yaron (2006) in the macroeconomics literature

[3] The relatively few exceptions include Heckman, Lochner and Taber (1998), Weiss and Lillard (1978), and Huggett, Ventura and Yaron (2006).

[4] The importance of this problem was recently emphasized by Solow (2001, p.174): "alternative ways of measuring human capital can make a big-time difference in the plausible interpretation of economic growth, so it is really important to come to some scientific agreement on the best way to deal with human capital as in input (and as an output, don't forget) and then to implement it."

first extreme is the implicit identification strategies adopted to construct an alternative to hours for a given country which take as given that quantities within an observable "type" of labor are constant and that all wage changes are due to changes in prices. The college premium literature provides a similar example where relative payments are typically taken as relative prices which implicitly assumes that relative quantities are constant. The life-cycle literature provides a contrasting example, representing the other extreme, where the life-cycle profile of payments is typically assumed to be the same as the life-cycle profile of the quantity of human capital which implicitly assumes that the price is constant over the life-cycle.

In this paper we address the identification problem directly and construct price series for three possible types of human capital associated with commonly used education groups: high school dropouts, high school graduates and college graduates. There is no simple solution to the problem. Some assumptions have to be made. Our assumptions are discussed in detail so that they may be contrasted with the implicit, and often in our view, extreme assumptions generally made in the literature. The price series that are constructed for these three education groups turn out to be surprisingly highly correlated over the period 1963 to 2003 despite their vast differences in skill level. The series also exhibit patterns that deviate substantially from wages, implying that wages are not good proxies for prices and that quantities of human capital associated with a given observable education type change over time. Both of these results have major implications for understanding the evolution of wages, wage premia and the human capital input in the aggregate production function (and hence, total factor productivity).

In Section 2 the basic identification issue is discussed. This is not a problem unique to human capital. The possible change in quantities of human capital associated with a given observable education type over time or across countries is identical to the problem of an unobserved change in quality over time in a product. A prominent example that has received much attention in the macroeconomic literature is the identification of an appropriate price series for various forms of physical capital inputs, particularly the input from computers. It is clear that conventional methods of constructing a measure of inputs over time in the case of computers fails very badly. Measures based on physical numbers, price or total value all drastically underestimate the computer input. The identification issue is taken very seriously in this literature. Unfortunately, the solution for human capital is more difficult than for many types of physical capital due to observability issues.

Section 3 presents two alternative identification approaches and implements them on data from the U.S. March Current Population Surveys (MCPS) covering earnings years 1963 to 2003. Using a flat spot method, that exploits variation over short intervals of time towards the end of the life-cycle in payments to the same cohort of workers, price series are constructed separately for the three human capital types. A standard unit method, which exploits variation in payments over time across cohorts for a group of workers considered to be a "standard unit" that is invariant across cohorts, is used to construct a price series for young high school dropouts. For this group a comparison is made between the two methods, which in fact yield very similar series. The price series all show substantial movement over the 1963 to 2003 period and the patterns are robust to a number of validity checks and sensitivity analysis. Perhaps the most surprising result is a very high correlation between the series from the lowest education group (high school dropouts) to the highest (college graduates). All of the series exhibit an increase in the price from 1963 to the mid-1970s followed by a substantial decline through the 1980s and 1990s that is interrupted by plateaus or recoveries coming out of the recessions of the early 1980s and the early 1990s.

The price series of Section 3 have many important implications for both microeconomic and macroeconomic issues. First, since the price varies over the life-cycle, the path of a cohort's wages or earnings does not identify the path of human capital. Second, since the series are highly correlated, there is little change in relative prices implying that much of the variation in the college premium is due to variation in the relative quantities of human capital associated with each observed education group. Third, the high correlation also implies that a homogeneous model may be a good approximation for macroeconomic models. This has the great advantage of a simplified and easily interpretable labor input. Finally, the use of this measure of the labor input suggests a very different path for total factor productivity (TFP) over the 1975-2003 period than is derived from conventional aggregate labor input measures. Each of these implications is explored in turn.

Section 4 examines whether the life-cycle pattern of quantities of human capital for each cohort implied by the price series is consistent with human capital theory and yields sensible cross cohort patterns. Section 5 re-examines the college premium in light of price series showing little change in relative prices. It shows that not only can the path of the average college premium be generated without large changes in relative prices, but the less well known age patterns, documented in Card and Lemieux (2001), can also be explained. Section 6 uses the estimates of the price series from Section 3 to construct measures of the total labor input and a new TFP series for the U.S. over the period 1975-2003. The results show that conventional quality adjustment to the labor input results in substantial underestimation in the growth of the true labor input, and hence a large overestimate of increases in TFP. Section 7 provides some final discussion and summary.

2 The Price and Quantity of Human Capital: Basic Identification Issues

In standard human capital models with competitive firms the hourly wage is the product of a price and a quantity

$$w_{it} = \lambda_t E_{it}, \tag{1}$$

where E_{it} is the amount of human capital supplied to the firm (number of efficiency units) by worker i in time period t, and λ_t is the rental price paid for renting a single unit of human capital (the price of an efficiency unit). The hourly wage is observed, but its two components are not. This is the fundamental under-identification property of human capital models.

In a homogeneous human capital model there is a single price, λ_t, and wages differ across workers in any given time period because of differences in the amount of (homogeneous) human capital they are supplying. Over time a worker's wage could change either because of a change in the quantity of efficiency units supplied, or because of a change in the price. Consequently, relative wages between any two observable "types" of workers - say college versus high school graduates - may change over time, but not because of a change in relative prices. All relative wage changes are due to relative changes in the quantity of efficiency units supplied by each type. This is the main consequence of the efficiency units approach in a homogeneous human capital model.

In heterogeneous human capital models, an efficiency units approach is retained within some exogenously defined worker type (e.g. college graduate) but is abandoned across types. With two worker types (e.g. college and non-college) there are two factors and two prices with wages given as follows (suppressing the individual subscript for convenience): $w^a = \lambda^a E^a$ and $w^b = \lambda^b E^b$ where λ^a and λ^b are the prices of efficiency units of type a and b, respectively, and E^a and E^b are the number of efficiency units of type a and b supplied by type a and b workers, respectively. Within type, the wage implications are the same as the homogeneous human capital model. For relative wages across types the implications are potentially different. Since there are now two prices, changes in relative wages between the two types reflect changes in relative quantities, E^a/E^b, and changes in relative prices, λ^a/λ^b.

The identification of the prices and quantities of human capital is a difficult problem in both homogeneous and heterogeneous human capital models. In heterogeneous human capital models used in the skill-biased technological change literature, it is implicitly solved by assuming that the quantities of human capital associated with any observed education level at any point in time are the same. This permits the identification of the skill price ratio from the wage ratio. However, this is a very strong assumption. It rules out selection in the choice of who goes on to higher levels of education, changes in optimal life-cycle accumulation of human capital within type, and technological change in human capital production functions.[5]

Since there is a strong correlation between measures of ability and the highest level of completed schooling, large secular changes in completed schooling levels may be expected to have significant selection effects on the average ability associated with each observed schooling level. Further, since major quality improvements due to technological change have been found for capital inputs such as computers, it is surprising that they are generally ruled out for the labor input. Technological improvement in human capital production functions can produce workers, of a given observed type such as education level, that can do more, in the same sense as more recent computers can do more. More recent vintages of physics PhDs, for example, may have received more value added through the education process, than earlier PhDs.

The identification problem and technological change in human capital production functions was discussed in a related context in Weiss and Lillard (1978) who tried to distinguish between "time" and "vintage" effects in the earnings of scientists. They documented the fact that there was a difference in the life-cycle path of earnings for the more recent vintages of scientists in the period they studied. The time effects can be interpreted as price effects, while the vintage effects can be interpreted as selection effects and technological improvements in human capital production functions, as well as the implied change in optimal investment over the life-cycle by each cohort. Since they were unable to employ a separately identified price series of the type derived in this paper, Weiss and Lillard (1978) were cautious about their interpretation of the vintage effects that they found. Nevertheless, they did conclude that there were substantial vintage effects over the period that they studied. This

[5]If technological change in human capital production is not taken into account, the labor input in aggregate production functions will be underestimated which results in an apparent technological improvement or TFP increase in the product market production functions. Similar mis-attribution can happen with capital mis-measurement. Greenwood, Hercowitz and Krusell (1997) investigate this issue and provide estimates to suggest that the magnitude in the capital input case is important. Estimates in Section 6 below suggest that the magnitude in the labor input case is also very important.

suggests that the assumption of no change in quantities within observable types may well be a bad one.

In this paper we consider two identification methods: the flat spot method which can be used with either homogeneous or heterogeneous models, and the standard unit method, which can be applied under certain conditions to identify prices and quantities over time within a homogeneous human capital model. The flat spot method, proposed in Heckman, Lochner and Taber (1998), is based on the fact that most optimal human capital investment models have the feature that at some point in the working life-cycle, optimal net investment is zero. The human capital of a given cohort over those years is constant. That is, there is a flat spot in the human capital life-cycle profile. Observing the changes in wages for the cohort over the flat spot, therefore, identifies the human capital price changes. In principle, this method can be used with any skill group to identify group specific skill prices.

The standard unit method works by finding an observable "standard unit" of human capital that is the same across time. In this case, observing the wage paid for a standard unit at different points in time identifies the price change. This is similar to the notion of finding a time invariant common unit for computers. The solution in the computer case is to assume that the common unit that represents the factor provided by all computers is calculations per second. That is, calculations per second are the efficiency units. The relevant price is the price of a standard computer defined as having a given number of calculations per second.[6] Given the assumption of the common unit, the identification problem in the computer case is made very simple by the fact that computations per second can be observed so it is not necessary to actually observe "standard" computers over time to identify the relevant price. In the human capital case it is necessary to observe a standard unit over time because efficiency units are not directly observed. In principle, an ideal standard unit would be a group of workers, drawn from the same region of the initial human capital endowment distribution in each period, who made no further investment in human capital. In practice, a group with the lowest exposure to human capital production functions, and the least addition to their initial human capital endowment has to be used.

[6] Of course it is a little more complicated than this, since there are other dimensions on which computers may differ, and a hedonic analysis is often performed, but the basic idea is that a meaningful comparison can be made that permits an aggregation in terms of a standard unit.

3 Estimates of the Price Series for Human Capital

Many aggregate models of the economy implicitly use a homogeneous human capital model with an aggregate labor input and a single price (aggregate wage). This has great interpretation and simplification advantages for macroeconomic growth analysis. However, the large microeconomic literature on increasing inequality in the U.S. and the links to increased estimated rates of return to schooling and skill biased technological change typically considers a framework with at least two skill levels. This is also an increasingly common feature in the macroeconomic literature which often divides the labor input into two types: skilled and unskilled.[7] In both literatures, the skill categories are defined with reference to observed education levels. For much of the literature high school graduates are compared with college graduates.[8] In this paper we estimate price series for three types of human capital or skills for the U.S. for the period 1963 to 2003. The three skills are all defined with reference to observed education categories for ease of comparison with the previous literature.

3.1 Data

The data source for the analysis is the annual March series from the Current Population Survey (MCPS). The MCPS records annual labor incomes for the year preceding the survey. Data from the March files for 1964 to 2004 were employed in the analysis to construct series covering earnings years 1963 to 2003. The MCPS has a number of advantages for this kind of analysis, especially the large sample size and the representative nature of the sample. However, there are a number of important issues that arise in using these data. Two major concerns are the consistency in the definitions of the key variables, such as earnings, hours and education levels, over the period, and the presence of top-coded and allocated values. With regard to the former there is a break in the series in 1974-75 that affects the way annual hours can be constructed. Because of this break, price series are estimated separately for the 1963-1974 period and the 1975-2003 periods. There is also a change in the way education levels are recorded in 1991. This is dealt with using the evidence from a sample of workers covered by both definitions, detailed in Jaeger (1997) and discussed in the Appendix. Problems with time varying top-coding in the earnings and in some years a high

[7] See, for example, Krusell *et al.* (2000)

[8] In Krusell *et al.* (2000) skilled labor is defined "as requiring college completion or better (at least 16 years of school)" (p. 1033); the remainder are unskilled.

frequency of allocated values are primarily dealt with by the use of medians instead of means and by dropping all allocated values. These and other data issues, as well as the solutions adopted for this paper, and robustness checks are discussed in detail in the Appendix.

Our overall sample includes all paid workers between the ages of 19 and 64 who have positive earnings in the previous year. This large sample is used to construct aggregate labor quantities. Subsamples based on gender, education and age are used to construct the price series under the two methods. The restrictions imposed on these subsamples are discussed below. Hourly wages are used as the wage measure and are constructed by dividing total annual earnings by total annual hours worked.[9] The hourly wages are then deflated using the Consumer Price Index (1982-1984=100).

3.2 Estimation Methodology

As noted above both homogeneous and heterogeneous human capital models assume an efficiency units structure at some disaggregated level. Under the assumption of competitive markets for each human capital type, log wages in these models for any individual i of a particular type are given by[10]

$$lnw_{i,t} = ln\lambda_t + lnE_{i,t}. \tag{2}$$

This implies that within each type the change in log wages between t and $t+1$ is given by

$$lnw_{i,t+1} - lnw_{i,t} = [ln\lambda_{t+1} - ln\lambda_t] + [lnE_{i,t+1} - lnE_{i,t}], \tag{3}$$

and, therefore, that the price change is given by

$$ln\lambda_{t+1} - ln\lambda_t = [lnw_{i,t+1} - lnw_{i,t}] - [lnE_{i,t+1} - lnE_{i,t}]. \tag{4}$$

Both the flat spot and standard unit methods estimate the price change by restricting estimation to observations where human capital levels do not change over time, i.e. where $[lnE_{i,t+1} - lnE_{i,t}] = 0$, so that the price change is equivalent to the observable wage change.

The flat spot method assumes that for each type there is an age range towards the end of the working life where efficiency units are constant. This is the point at which gross investment is just

[9]Issues regarding both annual earnings and annual hours worked are discussed in detail in the Appendix.
[10]Here we have suppressed the superscript notation delineating type.

sufficient to compensate for depreciation. This is a typical feature of Ben-Porath based models of optimal human capital investment over the life-cycle.[11] Aggregating over these observations, the price series can be estimated from observed wage changes

$$ln\lambda_{t+1} = ln\lambda_t + [lnw_{t+1} - lnw_t] = ln\lambda_t + D_{t+1}, \tag{5}$$

where $D_{t+1} = [lnw_{t+1} - lnw_t]$ is the difference in log wages between t and $t+1$ for a sample of observations which have the same efficiency units in t and $t+1$.

Initializing $\lambda_0 = 1$, the price series is estimated from successive log wage differences according to

$$\begin{aligned} ln\lambda_1 &= D_1 \\ ln\lambda_2 &= ln\lambda_1 + D_2 = D_1 + D_2 \\ . &= \\ . &= \\ ln\lambda_T &= D_1 + D_2 + ... + D_T, \end{aligned}$$

Repeated cross section data from the MCPS provide empirical counterparts to D_{t+1} as follows. Denote the age at the beginning of the flat spot as a. In year t the MCPS provides a representative sample of wage observations for individuals aged a in year t; it also provides a representative sample of wage observations for individuals aged $a+1$ in year $t+1$. Abstracting from mortality, these two observations provide a synthetic cohort. By assumption, efficiency units are constant for these individuals over the age range a to $a+1$, hence the difference in log wages in the sample of those aged $a+1$ in year $t+1$ compared to those aged a in year t, provides an estimate of D_{t+1}. Other estimates are provided by the difference in log wages in the sample of those aged $a+2$ in year $t+1$ compared to those aged $a+1$ in year t, or those aged $a+3$ in year $t+1$ compared to those aged $a+2$ in year t, etc. Given a flat-spot interval of m years, there are $m-1$ comparisons that can be used in the estimation.

The series detailed in this paper focus on the use of median wages, for reasons related to outliers, top-coding and allocated values in the MCPS data that are detailed in the Appendix, but very

[11] See Heckman, Lochner and Taber (1998), Huggett, Ventura and Yaron (2006) and Kuruscu (2006) for recent discussion of this feature of optimal life-cycle investment models.

similar series are obtained using average or median log wages. Most of the series reported in the paper were obtained by simply averaging these $m-1$ adjacent age median wage differences for each pair of years.[12]

The standard unit method uses the same estimating equation as the flat spot method,

$$ln\lambda_{t+1} = ln\lambda_t + D_{t+1},$$

where D_{t+1} is again the the difference in log wages between t and $t+1$ for a sample of observations which have the same efficiency units in t and $t+1$. But whereas the empirical counterpart to the D_{t+1} series for the flat spot method is obtained from following individuals in the same cohort over a period where their human capital does not change, the standard unit method replaces this by following a standard unit group across cohorts. The main estimates reported in this section use the log difference across years, t and $t+1$, in the median wage for adjacent birth cohorts of the standard unit group.[13]

3.3 Estimated Price Series from the Flat Spot Method

The flat spot regions are chosen to be towards the end of the working life, avoiding regions that may be influenced by retirement behavior. The sensitivity of the price series estimates to alternative flat spot regions is examined in detail. In order to implement the method it is necessary to choose the length of the flat spot, and hence the number of cohorts that can be used to identify price changes between any pair of years.[14] There is a tradeoff between the length of the flat spot and the sample size. The analysis reported here uses a flat spot length of 10 years, allowing the averaging of 9 cohort pairs across any two years. This is, perhaps, the minimum length that is feasible given the sample sizes. Since the adjacent age pairs are averaged across all nine pairs corresponding to the flat spot age range, the primary requirement is that averaged over these pairs, the change in efficiency units is zero. It is not necessary that the change in efficiency units is exactly zero for all pairs in the range; indeed, it may well be the case that for the earliest ages in the range the efficiency units may still have a small increase, and for the oldest ages efficiency units may have begun to decline.

[12] Alternative methods, such as taking the difference in wages between the pooled $m-1$ age groups, $a+1$ to $a+(m-1)$ in $t+1$ and the pooled $m-1$ aged groups a to $a+(m-2)$ in t, produced virtually identical series.

[13] As with the flat spot estimates, similar results follow from using average or median log wages, largely because they are both relatively insensitive to outliers, top-coding issues, and allocated value problems.

[14] A complication which we abstract from in this paper is that the flat spot may change over time.

Figure 1 plots flat spot series for the three education groups: high school dropouts, high school graduates, and college graduates.[15] Because there is a break in the series between 1974 and 1975, corresponding to the change in the way hours data are recorded in the MCPS, Figure 1 presents both subseries with 1974 and 1975 each normalized to 1. The series are all based on wage observations for males.[16] The flat spot ranges are 47-56 for high school dropouts, 49-58 for high school graduates, and 53-62 for college graduates. These flat spot ranges reflect standard theoretical restrictions that the profiles peak at later ages for the higher educated groups (roughly in proportion to the difference in age at the start of the working life) and that none of the ranges are pushed too far into any pre-retirement adjustment periods that may be influenced by substantial time varying labor supply and effort decisions.[17]

The most striking feature of Figure 1 is the close correspondence in the series for such diverse education groups as high school dropouts and college graduates. Over short intervals, the point estimates show some movement in relative prices by skill group, but any gaps disappear quickly. This is a surprising result in light of the large literature documenting and analyzing the increase in the rate of return to schooling, the relative wage of skilled workers, or the college premium, generally interpreted as an increase in the relative skill price. The implication of stable relative skill prices together with changing relative wages is that the relative median efficiency units of the different education groups has changed over time. In Section 5 below we argue that the sources of these changes are technological changes in human capital production functions, broadly interpreted, and selection effects due to large changes in the distribution of education levels across cohorts.

The other main feature of Figure 1 is a pattern of substantial price change over time. From 1963 to the mid-seventies there is a substantial price increase of 10 to 15 percent. From a peak in the mid-seventies there has been a major decline in the price, of about 20-25 percent. The pattern of the drop is interesting. It begins with a substantial decline until the recovery from the recession in the early 1980s. This is followed by a further decline until another period of recovery and plateau from the recession in the early 1990s. The price series for all of the education groups from high school

[15]All price and quantity series are available from the authors upon request.

[16]Females are excluded due to their larger fluctuations in labor force participation and the resulting added difficulty of defining an appropriate age range for their flat spot.

[17]The flat spot estimates may be influenced by a number of factors. Possible non-random participation due to retirement is perhaps the most obvious concern. However, biases for some groups could arise from contract wages and time varying incentive effects. All identification approaches based on observed wages are subject to these problems. We argue below that the evidence shows the estimates presented here, while potentially subject to some bias, are preferable to the estimates implied by the standard approaches in the literature.

dropouts to college graduates show the same broad sequence over all of these movements.[18]

3.4 Estimated Price Series from the Standard Unit Method

While the results for Figure 1 are robust to alternative wage measures, sample restrictions and estimation methods, they are calculated for a particular choice of reasonable flat spot ranges. The standard unit method provides an independent check on the range for the lowest education group: high school dropouts. In this section, the standard unit method is used to compute a price series for high school dropouts and this series is compared with alternative flat spot method series. The choice of the group is motivated by a simple human capital model in which each cohort is assumed to draw its initial endowment of human capital or ability from a relatively stable distribution.[19] Based on this endowment, individuals decide on a level of investment in human capital which is undertaken according to the human capital production functions that categorize the education and on-the-job training system that their cohort faces.

These production functions, broadly interpreted, are assumed to be subject to technological improvement over time, as for all other production functions. The correlation between the initial endowment and the level of human capital investment is assumed to be positive.[20] Under these assumptions the ideal standard unit group would be those members from the same lower tail portion of the initial endowment distribution that choose a zero level of further human capital production, i.e. a group with only their initial endowment. By definition this group would have the same median human capital level across successive cohorts as well as across time. In practice, there is no such group. Instead it is necessary to find the closest approximation. This requires the identification of a group where the addition to the initial endowment is the smallest, so that the human capital stock for this group would be closely proxied by the initial endowment.

[18]The price series can be calculated for many alternative wage measures and sample restrictions. As shown in the Appendix, the pattern in Figure 1 is robust to a wide variety of specifications. These include different minimum hours per week, weeks per year and annual hours requirements. They also include varying treatment of allocated or top-coded observations and the use of different wage measures with and without trimming. In general, the use of medians is preferred. There are both good theoretical and empirical arguments for preferring medians. They are less subject to problems from issues such as incentive pay and are insensitive to outlier problems that arise with some other measures. However, as shown in the Appendix, similar series are obtained from other wage measures, especially log wages which yield almost identical series in most cases.

[19]The rationale for assuming relatively slow change is the idea that this evolution is primarily genetic and that this is a slow process. However, the initial endowment may be influenced by other factors such as maternal and infant nutrition that, at least in some periods, may have a faster rate of change.

[20]This is not an unreasonable assumption as there is a high correlation between observed ability measures and educational attainment. For example, the correlation between highest degree completed and scores from the Armed Forces Qualification Test for individuals in the 1979 National Longitudinal Survey of Youth is 0.58.

In choosing this group there are several tradeoffs. While the main objective is to find a group that has the least contact with human capital production functions that may have been subject to technological change, it is also necessary to choose a group that has completed their education and become attached to the labor market, and a group such that the sample size is sufficiently large to yield reasonably precise estimates. Finally, it is also necessary to choose a group where the changes in the selection effects over the time period of the earnings data are small. The results reported here are for males that have less than 12 years of schooling (high school dropouts) and are 21-25 years old.[21]

As noted earlier, the identification strategy requires the mean initial endowment of the standard unit group to be time invariant. If the fraction in the chosen group varies substantially by cohort over the observation period, there would have to be some doubt over the validity of the identifying assumption. Figure 2 shows the time path of the fraction of each birth cohort between 1931 and 1967 at each of four possible categories of highest completed level of education. For the earliest cohorts about a third of the cohort were high school dropouts. This was followed by a rapid decline until the first post-war birth cohort when the fraction stabilized at around 13 percent. The earliest cohorts in our sample of 21-25 years of age are the 1938 to 1942 birth cohorts. Thus, apart from the first few years, the sample is obtained from successive cohorts with the same fraction of high school dropouts as required.

Figure 3 plots the estimated price series for three alternative wage measures and three alternative hours restrictions. The wage measures use mean wages, median wages, and mean log wages. The hours restrictions are: (R1) total annual hours at least 50, (R2) hours per week greater than 20 and weeks per year greater than 10, and (R3) hours per week greater than 20 and weeks per year greater than 20. All of the series exclude allocated values.[22] The patterns are all very similar, but the use of mean wage levels produces noisier series that are more sensitive to outliers. Overall, Figure 3 shows the very close correspondence between the series based on median or log wages, which are less sensitive to outliers, across a variety of hours and weeks restrictions.[23]

[21]Robustness checks were done with older and younger samples: 19-21 and 22-27, with very similar results. See Appendix Figure A3.

[22]Including allocated values adds more noise. In addition the allocated values include those allocated as part of a top-coding correction. These can give rise to outlier problems. Therefore, the allocated values should be used with caution. See the Appendix for further discussion, especially Figures A1 and A4 for examples.

[23]The plots are also very similar across alternative initial endowment age ranges and are insensitive to trimming, especially for the post 1974 period when the most detailed hours and weeks measures are available. See Appendix Figures A2 and A3.

Standard human capital theory suggests that high school dropouts have post-school human capital profiles that are relatively flat. This implies that the flat spot estimates should be relatively insensitive to movements in the flat spot age range on either side of the peak in the human capital profile. Figure 4 compares the standard unit estimate with estimates from flat spot series based on an average of early age ranges series, 45-54 and 47-56, and on an average of late age ranges series, 51-60 and 53-62. Comparison of the flat spot and standard unit series shows a strong relationship between the series obtained from the two independent methods.[24] Close inspection shows a tendency for a departure between the standard unit and flat spot series coming out of the recession of the early 1980s. This may be due to different recovery participation patterns of the younger high school dropouts (on which the standard unit estimates are based) and the older high school dropouts (on which the flat spot method is based.)

Overall, the results show similar profiles across a wide range of flat spot estimates; they all show initial increases followed by a decrease interrupted by two plateaus or recoveries. The relative insensitivity is consistent with expectations for the flat spot estimates for the high school dropout group, because standard theory implies that the profiles for this group are relatively flat. The relatively small difference for the older age range suggests that, at least for this group, the depreciation rate is relatively small. Finally, Figure 4 indicates that the standard unit series is a little closer to the early than the late flat spot series.

3.5 Sensitivity Analysis for High School and College Graduates

Overall, the close similarity of the estimates of the lowest (high school dropout) skill price series obtained from the two independent methods - one using across cohort variation at a young age, and the other using within cohort variation at much later ages - provides some evidence of robustness of these forms of identifying human capital prices. A similar comparison cannot be made for groups with higher levels of education as their period of schooling and significant post-schooling investment is longer, making them unsuitable candidates for the standard unit method. In addition, their level of post-school investment is likely to be higher, making the flat spot estimates more likely to be sensitive to the age range chosen for the flat spot. In this section, the relative patterns of series obtained using deviations from the flat spot ranges used in Figure 1 are examined.

[24] Figure 4 uses the series based on data that exclude allocated values and impose the strongest hours and weeks restrictions, but the estimates are similar for the other specifications.

Standard human capital models predict three features of the life-cycle profile of human capital stocks that are of interest. First, the profile is concave with the largest increase in the early years, rising to a peak and then declining as depreciation comes to dominate the gross investment. This implies that choosing a flat spot interval that is too early results in price change estimates that are upward biased. That is, they include some positive change in efficiency units, as net investment is still positive. Conversely, choosing an interval that is too late overestimates the price change because of the depreciation. Ideally the flat spot interval brackets the peak such that for the sample as a whole the change in efficiency units is zero. Second, the peak occurs at later ages for more educated groups. This suggests choosing a relatively late interval for the college group. Third, post-school investments are generally predicted to be smaller, or even zero, for lower education groups compared to college graduates. Thus, the series for college graduates should be more sensitive to moving the flat spot interval than for high school dropouts. In fact, Figure 4 showed that the series for high school dropouts is quite insensitive to the flat spot range. Examination of the higher education groups shows, as expected, greater sensitivity.

The flat spot for high school graduates in Figure 1 is 49-58, which was set to start 2 years later than for high school dropouts; Figure 5 plots the series for an earlier age range, 47-56, and a later age range, 51-60. The profiles show the same relation as for high school dropouts: as expected, moving to an earlier age range steepens the earlier rising phase of the series and flattens the later falling phase. Moreover, as expected, the sensitivity is increased relative to the high school dropouts. In Figure 1, the flat spot for college graduates is 53-62, which was set to start 4 years later than for high school graduates. Figure 6 shows what happens as the age range is moved back, first to 51-60, then all the way back to the high school dropout range, 47-56. The expected tilting is again apparent; the increasing phases are steepened and the declining phases are flattened. Since the tilting direction is the same for all education groups, moving the flat spots together, especially for high school graduates and college graduates, tends to keep the price series moving together.

An additional test of the appropriate flat spot range for college graduates can be made by examining the cross-section log wage and median wage profiles for the pooled years 2001-2003. The slopes of cross section profiles are potentially biased because of the cohort effects associated with increasing age. There are two cohort effects: different selection from the initial endowment distribution and different human capital production functions. Assuming that the technological change in human capital production is non-negative, the cohort effects impart a downward bias on the slope over the age range 45-57 for the 2001-03 cross-section. The relevant birth cohorts change from 1956-58 to 1944-46 over this age range and time period, and, given the increase in college attainment over these cohorts (see Figure 2), a negative selection effect is combined with a non-negative technological change effect. The peak of the cross section wage profile is around 56 suggesting that the peak of the human capital profile is no earlier than 56. Thus our use of 57.5 as the mid-point of the college flat spot range in Figure 1 is consistent with this evidence.

4 Human Capital Prices and Life-Cycle Analysis

The early literature on human capital in a life-cycle context studied the implications of optimal investment in human capital for log wage profiles by age or experience. Following influential papers by Ben-Porath (1967), Heckman (1976), Rosen (1976) and others, human capital theory became the dominant framework for analyzing life-cycle earnings. This framework has spread from its base in labor economics and is increasingly used in the modern macroeconomics literature. Recent examples include Huggett, Ventura and Yaron (2006) and Guvenen and Kuruscu (2007).[25] Empirical examination of experience profiles, based on the human capital framework, has a long tradition going back to Mincer (1974). The Mincer inspired literature has recently been re-examined by Heckman, Lochner and Todd (2002). The large number of papers indicates the continuing importance of this topic for economists in understanding wage patterns. With the aging of the workforce in most developed countries, the importance of understanding how human capital evolves over the life-cycle has increased.

That said, the fundamental identification problem in human capital models discussed in Section 2 presents a major problem for interpreting these profiles. In the standard life-cycle human capital model of the Ben-Porath type, observed wages are the product of a price and quantity of human capital supplied to a firm. Identifying the life-cycle profile of the (supplied) quantity of human capital from wage data requires identification of the price. Even with cohort data, aging a cohort over time does not identify the time profile of a worker's supplied human capital unless the price is constant over the lifetime. In almost all of the literature on life-cycle earnings a constant price is a maintained assumption.[26] For example, the relevant chapter in the *Handbook of Labor Economics*

[25] A separate but related development in the literature has been the estimation or calibration of general equilibrium models of human capital accumulation over the life cycle. Examples include Heckman, Lochner and Taber (1998), Imai and Keane (2004), Lee (2005) and Hansen and Imrohoroglu (2007).

[26] The main exception is Heckman, Lochner and Taber (1998). More recently Huggett, Ventura and Yaron (2006)

has no discussion of time varying prices.[27] Under the constant price assumption the life-cycle wage profile is the same as the life-cycle (supplied) human capital profile.[28] The pattern of life-cycle wages can then be used to directly test human capital model predictions concerning the life-cycle profile of human capital.

Kuruscu (2006) is a recent example of life-cycle analysis that takes this approach. Marginal costs of post-school investment, based on the Ben-Porath model, are estimated with the explicit assumption of a constant rental rate over the life-cycle. This assumption is used to infer from wage profiles that growth in human capital over the life-cycle stops relatively early and leads to the conclusion that training has a small contribution to lifetime income. However, the estimates presented in Section 3 strongly indicate that the rental price is not constant, and that a constant price assumption will lead to misleading conclusions about the life-cycle profile of human capital. In fact, the evidence suggests that in the last three decades in the U.S. the price movements have been large.[29] In this section we compare the implied life-cycle human capital profiles for a variety of birth cohorts whose wages are observed in the 1963-2003 period using the price series of the preceding section with the implied profiles using the standard constant price assumption in the literature.

4.1 Life-Cycle Human Capital Profiles

Under the constant price assumption the life-cycle wage profile is the same as the life-cycle (supplied) human capital profile. This is plotted for males in the lowest skill level, high school dropouts, by selected cohorts spanning the earnings observations in the MCPS for 1963 to 2003 in Figure 7a.[30] The profiles are difficult to make sense of within a standard Ben-Porath model. They are all very different shapes. The 1925 cohort appears to have continued to grow quite rapidly to age 50; the 1937 cohort shows extremely rapid growth (almost as much as college graduates) to a peak around age 40. In contrast, the 1946 birth cohort shows rapid growth in the twenties but peaks around age 30

relaxed the constant price assumption and assumed a constant rate of growth for the rental rate on human capital equal to the average growth rate in mean real earnings. Guvenen and Kuruscu (2007) take a similar approach in calibrating their model of inequality.

[27] See Weiss (1986).

[28] In the Ben-Porath model, in each period of positive investment the individual supplies part of their human capital to the market and part to the production of more human capital. After the period of specialization, the part supplied to the market may be the largest part, and in some cases, almost all the human capital stock of the individual at that point, but in general the supplied and total stocks differ until gross investment is zero.

[29] The evidence also suggests that the movements in the price have not been monotonic. Thus assuming a constant growth rate in the price, as in Guvenen and Kuruscu (2007), would also result in misleading conclusions.

[30] All of the life-cycle analysis is done for males only.

and the 1958 cohort is flat throughout. The profiles often cross. Moreover, the most recent cohorts show low levels of human capital relative to the earlier cohorts. Some decline could be expected between the 1925 and 1937 cohorts due to selection. In Figure 2, the fraction of the high school dropouts in a cohort shows a substantial decline up to the 1946 cohort. Given a positive correlation between initial endowment/ability and completed education,[31] the decline in the cohort fraction of high school dropouts would be accompanied by a decline in the median initial endowment/ability among the high school dropouts up to the 1946 cohort. However, after 1946 the fraction is stable. It is, therefore, surprising that the 1958 cohort appears to have so much less human capital than the 1946 cohort when it should be drawing from the same point in the initial endowment distribution.

Figure 7b shows the implied life-cycle human capital profile for the same group using the price series from Section 3 to identify the profile. Using the heterogeneous human capital model, the separate price series for high school dropouts in Figure 1 is used to identify the human capital profiles for high school dropouts by cohort. Even though the profiles are plotted with no smoothing in any of the underlying series, it is apparent that the pattern is now much closer to a series of cohort profiles all with similar shapes and more readily interpretable within a Ben-Porath model with slow changes in production function parameters and/or initial endowments. Instead of drastically varying shapes in the early twenties to early thirties age range, and drastically varying peaks from age 30 to age 50, the profile shapes are much closer to each other and to a standard concave profile. There remains some indication of a small drift down over time in the profiles. The 1958 cohort still appears somewhat below the 1946 cohort, but compared to Figure 7a the gap is much smaller and not always negative and the slopes are quite similar.

Figures 8a and 8b repeat the analysis for high school graduates. The same contrast appears as for high school dropouts, though the pictures are even clearer due to the larger sample sizes which make the profiles smoother. Figure 8a shows the same confused pattern as Figure 7a. There is a lot of crossing in the profiles and the 1958 profile is dramatically worse than the 1946 profile, with a twenty to thirty percent difference for most of the twenties and thirties. In contrast, Figure 8b shows the classic Ben-Porath profile shape for all birth cohorts and much more similarity in the 1946 and 1958 cohorts.[32]

Figure 2 showed a marked secular trend over birth cohorts in the fraction of the birth cohort

[31] See footnote 20.

[32] An almost identical contrast occurs for the some college group. The results are available on request.

that were high school dropouts. From about one third of the population in the earlier birth cohorts, the high school dropout group fell to about 13 percent by the 1946 birth cohort, where it stabilized. There is much less variation in the fraction of high school graduates. Another interesting feature of Figure 2 is the path of the fraction of college graduates. This fraction peaked in the 1946-1949 birth cohorts. The some college group follows a similar pattern.

Given the patterns in Figure 2, the high school graduate group is subject to selection from two directions: upward movement into the group from high school dropouts, and upward movement out of the group into some college and college graduates. Given the evidence of the positive correlation between ability and education level, this suggests that the high school group is subject to negative ability selection when high school dropouts are declining and when some college and college graduates are increasing. Both of these conditions were in effect up to the 1946 birth cohort. It is interesting that the profiles for the high school graduates remain quite close together across the birth cohorts, suggesting that this negative selection effect was offset by slow technological improvement in human capital production. That is, while the initial endowment may have been declining, this was offset by a slow upward trend in the value added by the schooling system.

The life-cycle profiles for the college graduates are plotted in Figures 9a and 9b. Since Figure 2 shows a substantial increase in the fraction of college graduates from the 1931 to the 1946 birth cohorts, the positive correlation between ability and education level suggests a negative ability selection over this period, followed by a reversal of the selection effect as the fraction began its decline until the most recent cohorts. Figure 9b shows the expected relative improvement between the 1958 and the 1946 cohorts compared to the 1946 versus the 1937 cohort. However, since the earlier cohorts show roughly similar profiles, the vintage improvement in college knowledge appears to have been just enough to offset the negative selection effect. By the 1946 birth cohort, both selection effects and technological improvement predict an upward shift in the profiles, but this is only apparent in Figure 9b where the estimated price series is used. Overall, the use of the price series from Section 3 provides a picture of cohort change over time in the human capital profiles that is much less erratic, and much easier to explain in an optimal human capital life-cycle investment model with moderate changes in the production function parameters over time.

5 Human Capital Prices, Inequality and the College Premium

The cohort analysis of the previous section provides a useful test of the credibility of the price series estimated in Section 3. While these price series show small differences across education groups, the most noticeable feature of the series is their high correlation. This implies little change in relative skill prices. How can this be reconciled with the well documented increase in the college premium in the 1980s and 1990s? The basic fact is that various summary measures of the difference in wages or annual earnings for those with a college degree compared to, say, high school graduates did increase substantially. For example, Card and Lemieux (2001, p.705), hereafter CL, report in increase in the gap "from about 25 percent in the mid-1970s to 40 percent in 1998." The standard approach to analyzing this increase in inequality is to posit a heterogeneous human capital model in which college graduates are one type of human capital and high school graduates are another type and to attribute the change in the gap entirely to a change in the relative prices of these two types of human capital. However, as discussed in Section 2, this implicitly imposes the strong identification assumption of no change in the relative quantities. It rules out both technological change in human capital production functions and selection effects which would be expected over periods of substantial changes in cohort education levels. Moreover, it implies that the path of the college wage gap should be the same for all ages since all ages would be subject to the same relative price changes, which is strongly inconsistent with the data.

There is, in fact, a very strong age pattern to the evolution of the college wage gap. It is largely confined to younger workers. Figure 10 shows the evolution of the college premium for males from the MCPS data for the two different age groups, 26-30 and 46-60, used in Figure 1 in CL. It plots the log of the ratio of median hourly earnings of college graduates to high school graduates and shows a very similar pattern to Figure 1 in CL. The recent premium increase is largely confined to younger workers (26-30), where the ratio declines slightly before 1980, then increases between 1980 and 1995. The log of the ratio of median hourly earnings of college graduates to high school graduates, plotted in Figure 10, can be decomposed into relative quantity and price components as follows

$$ln(\frac{w^c}{w^h})_t = ln(\frac{\lambda^c}{\lambda^h})_t + ln(\frac{E^c}{E^h})_t,$$

where $\frac{w^c}{w^h}$ is the ratio of wages of college graduates to high school graduates, $\frac{\lambda^c}{\lambda^h}$ is the ratio of prices and $\frac{E^c}{E^h}$ is the ratio of quantities. Figure 11 presents this decomposition for the young age group

(26-30).

The relative price path in Figure 11 uses the heterogeneous price series from Section 3. It shows some decrease in the relative skill price to 1980 and an increase thereafter, though the movement is quite restricted reflecting the high correlation of the price series for the different education groups estimated in Section 3. Most of the increase in the relative wage for college graduates over the 1980 to 1995 period for this age group comes from the increase in the relative quantities. Comparing the 1980-1982 period with the 1995-1997 period there is a change in the relative log wage ratio of .232. The decomposition shows that .168 comes from the quantity change and .064 from the price change. Thus, the price change only accounts for about 28 percent of the observed wage premium change. Over 70 percent is due to the relative quantity change.

The path of the relative quantities can be explained by selection effects implied by the positive correlation between ability and education levels and technological improvement in human capital production functions. The birth cohorts for the older age group in CL ranged from 1910-1924 for the 1970 observation in CL's Figure 1 to 1935-1949 for the 1995 observation. Thus, throughout the period there is a negative ability selection effect implied by the increasing fraction of college graduates in successive cohorts shown in Figure 2. In contrast, Figure 2 shows that for the younger group there is a negative selection up to about 1975. After that the selection effects are positive. For the younger group Figure 11 shows the resulting path of relative efficiency units.[33] During the earlier period of a strong increase in the fraction of the birth cohort becoming college graduates, there were two competing forces influencing the average quantity of human capital in a college graduate: a negative force from the selection effect, and a positive force from technological improvement. From Figure 11 we see that the negative force dominated. Once the fraction of a birth cohort becoming college graduates began its decline with the late 1940s birth cohorts, the selection and technology effects work together to increase the relative quantity of human capital embodied in college graduates compared to high school graduates.

Overall we find that relative quantity changes dominate relative price changes in explaining the observed changes in relative wages. While there is a role for relative prices changes, the common assumption that all wage differentials are driven by price differentials is not supported by the evidence and results in misleading conclusions.

[33]The relative wage path closely follows the relative efficiency unit path in Figure 11 because the relative price path is approximately constant.

6 Human Capital and Growth: Measuring the True Labor Input

Assessing the contribution of human capital to growth requires a measure of the labor input or inputs. The evidence from Section 5 of large changes in the quantity of human capital associated with various education levels has important implications for measuring the true labor input. The earliest measures used in the literature were aggregate hours of labor. However, hours of different workers are typically not comparable in terms of their labor input. A worker with more human capital supplies more labor input. Several countries have attempted to get better measures by refining the construction of their aggregate labor input indices, previously measured by aggregate labor hours, to take into account changes in the composition of the labor force. The rapidly increasing average education levels in the workforce was a major reason for this initiative.

A homogeneous human capital model has great benefits as the conceptual basis for defining an aggregate labor input and corresponding aggregate wage. The single price feature of the model provides an elegant solution to the definition of the aggregate wage: the price of an efficiency unit of homogeneous human capital. The single type feature provides a similarly elegant solution to defining the aggregate labor input: the quantity of efficiency units of human capital. This quantity can be obtained by a simple aggregation of hours supplied weighted by the efficiency units of each worker.

The issue is quite different if human capital is heterogeneous. If human capital is heterogeneous and the types are observationally identifiable by, say, education level, there is in fact little to be gained by arbitrarily aggregating the different types. One could just directly model the production function with all of the different human capital types.[34] In this section, we examine the construction of measures of the true aggregate labor input under the single price series estimated in Section 3, and measures of the true labor input by type (identified by education group) under the separate price series by education level. These measures are compared with the standard aggregate measures in the literature.

6.1 Aggregate Labor Input: Composition Adjusted Hours

Most standard aggregate labor input measures are some form of composition adjusted hours. The BLS provides the main official composition adjusted series for the U.S. as part of its Multi-factor Productivity (MFP) Program. The motivation for the series is described in BLS Bulletin 2426

[34] A recent example of this is Johnson and Keane (2008) who estimate a model with 160 different types of human capital differentiated by gender, education, age, and occupation.

(1993). Prior to this series, labor input had been measured by the total hours of all workers. It was widely recognized that "the effective quantity of labor input does not rest solely on the total number of hours worked by members of the U.S. labor force but also on characteristics of the labor force." (p. iii). Following the recommendations of a National Academy of Sciences Panel to Review Productivity Statistics in 1979 the BLS developed a weighted measure of total hours focusing on the skill level of workers as reflected in education and job market experience levels. This measure is used in the construction of the BLS MFP index.

The BLS measure is described in detail in the BLS Handbook of Methods (1997), and in BLS Bulletin 2426 (1993), which reported the first estimates. It is based on a Tornqvist chained index of weighted hours of workers classified by skill and demographic characteristics. The hours measures used in the original BLS Bulletin 2426 (1993) study for the period 1968-1990 were obtained from the MCPS. For the current series for the BLS MFP Program, hours are obtained mainly from the BLS Current Employment Statistics (CES) program, based on establishment surveys. They are supplemented by data from the CPS and other sources for groups not covered under CES. The weights are the shares of total compensation for each type of worker classified by skill and demographic characteristics, and the weights are allowed to vary each year.

Prior to the development of the BLS measure, a number of authors had developed and published composition adjusted aggregate hours series.[35] The most well known current version of these is the Jorgenson series for the U.S. private economy, 1977-2000.[36] There are some differences in the details of the methods and coverage, but the basic methodological approach is the same for both the Jorgenson and BLS series, and the two series are very similar for the 1977-2000 period. The series are given in Table 1. The first two columns show aggregate hours for the private economy. The coverage is a little broader for Jorgenson's series, but the pattern is the same. Overall growth in aggregate hours from 1977 to 2000 for the Jorgenson series is 53.39 percent compared to 50.42 percent in the BLS series. The next two columns report the composition adjustment factor with 2000 as the base.[37] The adjustment factors for the Jorgenson and BLS series are almost the same. The final three columns report the composition adjusted labor input. In the first of these, the Jorgenson series is higher than the BLS series, despite the similar composition adjustment factors, because of

[35] See, for example, Chinloy (1980), Denison (1985), and Jorgenson, Gollop and Fraumeni (1987).

[36] Available at: http://post.economics.harvard.edu/faculty/jorgenson/papers/lqualprivate.xls

[37] The published Jorgenson series has 1996 as the base and was adjusted to 2000 to match the base year for the published BLS series.

the wider coverage. The last two columns show that, when the Jorgenson series is scaled to the BLS series in 1977, the two labor input series look almost the same.

The growth in the labor input series that adjusts for composition is substantially higher than the aggregate hours growth. Using the BLS figures in Table 1, the hours growth is 50.42 percent, but the composition adjusted input growth is 66.68 percent. Thus, the changing composition contributed almost one quarter of the total growth in the composition adjusted input. Since the growth rate using composition adjusted hours is almost one third higher than when using hours, the use of hours in constructing the MFP would substantially bias the change in the index over this period. Adjusting hours for composition changes is clearly important. However, because it ignores technological change in human capital production and endogenous choice of human capital investment, the composition adjusted series itself is subject to bias. For example, in the presence of technological improvement and increased life-cycle investment associated with the increased labor market attachment of women, composition adjustments to aggregate hours, like those of the BLS or Jorgenson's, still underestimate the true labor input.

6.2 Aggregate Series and Homogeneous Human Capital

With homogeneous human capital a total efficiency units series can be calculated simply by dividing total wage payments by the (single) price series. In this section an efficiency units series is compared with standard aggregate labor input measures. For ease of comparison, we use a single data set, the MCPS, to construct three measures of the labor input: an aggregate hours measure, a BLS/Jorgenson style composition adjusted aggregate hours measure, and the efficiency units measure implied by the price series derived in Section 3.[38] Comparisons between these three measures have a simple interpretation within the homogeneous human capital model. Divide hours of labor into J types (skill groups) where within type all members are the same "quality," i.e. have the same efficiency units per hour. For the BLS these are groups based primarily on sex, education and experience.

Let E_{jt} be efficiency units per hour for a member of group j, and h_{jt} be the total number of hours of type j. Total efficiency units in period t, N_t, are then

$$N_t = \sum_j N_{jt} = \sum_j E_{jt} h_{jt}.$$

[38]The full sample is used for these calculations including both males and females.

Let W_{jt} be total payments to members of group j in year t. Total efficiency units for any group j can then be computed simply by dividing the total expenditure, W_{jt}, by the price, λ_t, estimated in Section 3. Aggregating across types, the total efficiency units series N_t, is simply total expenditure across types, $W_t = \sum W_{jt}$, divided by λ_t.

The BLS measure uses a Tornqvist chained index. The construction of a Tornqvist chain index of composition adjusted labor input is as follows. For group j the ratio of the labor input in year t to the input in $t-1$ is by definition: $L_{j,t/t-1} = E_{jt}h_{jt}/E_{jt-1}h_{jt-1}$. Aggregating across groups, the Tornqvist chained index (ratio) of the total labor input in year t to the input in $t-1$ is given by weighting the ratios of the groups as follows

$$L_{t/t-1} = (L_t/L_{t-1}) = \prod_j (E_{jt}h_{jt}/E_{jt-1}h_{jt-1})^{\omega_{jt}}$$

or

$$lnL_{t/t-1} = \sum_j \omega_{jt} ln(h_{jt}/h_{jt-1}) + \sum_j \omega_{jt} ln(E_{jt}/E_{jt-1}), \tag{6}$$

where the weights, ω_{jt} are the shares of the groups' efficiency units in total efficiency units, averaged over the adjacent periods

$$\omega_{jt} = (W_{jt}/(\sum W_{jt}) + W_{jt-1}/(\sum W_{jt-1}))/2.$$

The BLS series from an initial period zero to t follows by chaining the ratios, $L_{t/t-1}$, to get the change from zero to t

$$\Delta L_{t/0} = L_{t/t-1}L_{t-1/t-2}....L_{1/0}$$

so that the value in any period t is given by

$$L_t = L_{t/t-1}L_{t-1/t-2}....L_{1/0}L_0,$$

where L_0 is some normalized value in period zero.

Note that, the BLS series implicitly assumes that there is no change in efficiency units per hour within groups, i.e. that $E_{jt} = E_{jt-1}$, which sets the second term in equation (6) to zero. The first term in equation (6), the BLS measure, is simply a composition adjusted hours index: a weighted sum of each groups hours change. Thus, the series ignores the second term which is the weighted sum of the percentage changes in average efficiency units per hour, or quality, within group. This term is non-zero whenever any group has a change in average efficiency units per hour over time, i.e. an average quality change via technological change, selection effects or cohort optimal investment changes.

Table 2 compares the alternative labor input series estimated using the MCPS. The BLS-style (Tornqvist) composition adjusted series was calculated as described above, using 120 groups classified by education, age and sex for a population of private paid workers aged 20-64.[39] The first column reports the aggregate hours estimate from the MCPS. The growth in hours is substantially less than the growth in the composition adjusted hours which are reported in the third and fourth columns, as expected from Table 1. However, the growth in composition adjusted hours is itself substantially less than the growth in efficiency units reported in the final column of Table 2. The same series for the population of all paid workers, 20-64, are reported in Table 3 and show a similar pattern. Composition adjusted hours grow faster than the unadjusted series because of the increased education level in the population. Efficiency units grow faster than composition adjusted hours because the composition adjustment ignores technological change and changing investment patterns.

The magnitudes of the differences are very large: efficiency units grow almost twice as fast as hours. The magnitudes of the differences in the growth rates are shown in Table 4. Unadjusted hours of private sector paid workers for the period 1977 to 2000 has a growth rate of 67.72 percent; composition adjusted hours grew by just over 90 percent. The composition adjustment thus produces a labor input growth that is about one third higher than the unadjusted hours growth. However, the growth in efficiency units is 118.48 percent. The standard composition adjustment to hours is therefore less than half of the full adjustment to aggregate hours that is necessary to estimate labor input growth between 1977 and 2000. The pattern is the same for the sample of all paid workers.

Table 4 reports the growth rates of alternative labor input measures by sex. The BLS method for total hours uses compensation shares to weight the growth of each type of hours, including male versus female. The logic of this weighting suggests that to get separate totals for males and females, the total labor input estimate should be split between males and females according to the compensation shares in the year, assuming no discrimination.[40] The results for this method are

[39] The March supplement weights were used for all the total estimates.

[40] The use of compensation shares in the BLS method implicitly assumes that the wage rate for females reflects the true marginal product, i.e. that there is no discrimination. The estimates of total efficiency units in Tables 2 and 3 are also based on this assumption. If discrimination creates a significant difference between the wage and the marginal product of female labor, without adjustment the total efficiency units series would be underestimated, and the degree of underestimation would vary over time as the degree of discrimination varied. In a standard employer discrimination

denoted BLS (A). An alternative is to apply the BLS method separately to estimate compensation share weighted male hours growth and compensation share weighted female hours growth. The results in this case are denoted BLS (B). By construction, the relative rates of growth in the BLS (B) measures of the labor input by sex simply reflect the relative rates of growth of hours.

Human capital theory predicts that the increased labor market attachment of females has increased female human capital investment. The substantial literature on female wage differentials has documented this increase, which has taken many forms, including more market oriented human capital investments for females at college. This increase has resulted in an increase in the total labor input of females by all measures, including total hours. Total hours for female private workers increased by 100.10 percent from 1977 to 2000, which is double the growth in male hours of 49.50 percent. The same pattern occurs for all paid workers: female hours increase by 90.98 percent and male hours by 42.75 percent. The growth in efficiency units (EUS) for females, however, is particularly pronounced. From 1977 to 2000 the growth in efficiency units for females is 202.98 percent, which is double the growth in hours. In contrast, much smaller rates of growth are estimated using the BLS style measures: 163.93 percent for BLS (A) and 137.68 percent for BLS (B).

6.3 Aggregate Series and Heterogeneous Human Capital

In addition to the Jorgenson series and official aggregate labor input measures, other measures of aggregate input, focusing on composition adjustment, have been constructed in a variety of studies in the business cycle literature and the macroeconomics literature more generally. Studies of wage cyclicality, recently reviewed in Bowlus, Liu and Robinson (2002), are concerned with the effects of a downward composition bias on the estimates of the correlation between wages and the labor input over the cycle. In tackling the problem of composition bias, these studies implicitly or explicitly construct aggregate wage and hours measures that are designed to address quality variation in the human capital input over the cycle induced by composition changes. Examples of include Hansen (1993) and Kydland and Prescott (1993) for a total economy aggregate, and Katz and Murphy (1992) and Krusell et.al. (2000) for aggregates by skill group. These series are all efficiency units based, either for the economy as a whole or within skill group. They all use a composition adjustment

model the true efficiency series is calculated separately for males and females. For males it is calculated as before by dividing total wage payments by the estimated price; for females, the total wage payments first have to be scaled up according to the amount of the discrimination. If, for example, discrimination against females was 10 percent in 1975, declining to zero in 2001, the growth in total efficiency units from 1975 to 2001 for paid workers would have been about 132 percent instead of the 139.65 percent reported in Table 4.

approach, and therefore suffer from the same type of bias as the BLS and Jorgenson estimates, to which they are related.[41]

Heterogeneous models, such as Krusell et. al. (2000), abandon the assumption of a single type of human capital, but maintain an efficiency units assumption within type for the purposes of aggregation. To examine the magnitude of the underestimate of the labor input using the fixed weight efficiency units methods we constructed efficiency unit aggregates by skill and in total using a method analogous to Krusell et. al. (2000) and Kydland and Prescott (1993). These fixed weight methods are similar to the BLS and Jorgenson methods in that they aggregate the hours of different types of workers using average wages as weights, classifying the different types of workers according to age, sex and education.

While the BLS and Jorgenson methods use chained indexes of weighted hours growth rates with varying weights, the fixed weight methods simply compute the hourly efficiency units of a worker of any given type as the average hourly wage of workers of that type. Applying the fixed weight efficiency unit method to all workers yields a total labor input, I_t, in period t of

$$I_t = \sum_j (\bar{W}_j h_{jt}), j = 1, 2, ...J,$$

where h_{jt} is total hours of workers of type j in year t, $\bar{W}_j$ is the average wage of workers of type j in the reference year (or averaged over all years), and J is the number of worker types. Similarly, total labor inputs for particular skills defined by subsets of the J worker types, such as unskilled (U) and skilled (S), are given by

$$U_t = \sum_{j \epsilon U} (\bar{W}_j h_{jt})$$

and

$$S_t = \sum_{j \epsilon S} (\bar{W}_j h_{jt}).$$

The estimated input growth from the fixed weight methods are presented in Table 5. The top half of Table 5 reports the estimates for an aggregate labor input across skills. The rates of growth of hours, efficiency units and the BLS style measure are repeated from Table 4. The results show that the composition adjustment applied to aggregate hours implied by the fixed weight approach is

[41] Krusell et. al. (2000) use the weights from the year 1980 for the whole period 1964-1993; Kydland and Prescott (1993) use the weights from averaging across all years.

almost identical to the BLS style methods and therefore has the same degree of underestimation of the increase in the labor input.

The lower half of Table 5 reports separate estimates for skilled and unskilled workers, defined analogously to Krusell et. al. (2000),[42] using weights averaged across years as in Kydland and Prescott (1993). The results show that within both skill types defined by observed education level, the fixed weight estimates produce growth rates that are lower than the efficiency units estimate. The underestimation problem is larger for the skilled group, but even for the unskilled efficiency units grow much more than indicated by the fixed weight estimates. The results from Table 5 provide further indication that composition adjustment methods may substantially underestimate the rate of growth of the labor input. Fixed weight methods, by construction, do not permit total efficiency units of labor to increase if the demographic composition does not change, except through hours. This likely has little effect for cyclical analysis, but for longer term secular growth or cross country comparison, it is potentially extremely important. One important consequence is the potential for serious overestimation of MFP and underestimation of the role of human capital in growth.

6.4 Consequences for Multi-factor Productivity

A major motivation for the construction of quality adjusted labor input series is that the use of unadjusted hours results in a substantial bias in the estimation of MFP or TFP. Since changes in MFP are defined as the residual change in output that cannot be accounted for by the changes in the inputs, the estimates of these changes depend on the estimates of the changes in the inputs. Define l as the growth in the true labor input, h as the growth in aggregate hours, and h^c as the growth in composition adjusted hours. Then the overestimate of the growth in MFP from using h in place of l is $s_l[l - h]$ and the overestimate of the growth in MFP from using h^c in place of l is $s_l[l - h^c]$ where s_l is the share of labor in total costs.

The results in Tables 2-5 indicate that adjusting for composition falls a long way short of a full quality adjustment, since it cannot capture technological change in human capital production or increased human capital investment by females. For the U.S. for the period 1975 to 2001, the growth in hours underestimates the growth in efficiency units of private sector paid workers by 73.34 percentage points. Since the share of labor in total costs is roughly two thirds,[43] this implies an

[42]See footnote 8 for the skill group definitions.

[43]The BLS estimates for labor share in total cost are 0.678 in 1975 and 0.686 in 2001.

overestimate of the growth of MFP of almost 50 percentage points. Using composition adjusted hours underestimates the growth in efficiency units by 47.76 percentage points. Hence, this adjustment implies an overestimate of the growth of MFP of 30 percentage points. The BLS estimate of MFP growth in the private business sector between 1975 and 2001 is 23.76 percent.[44] The results therefore suggest that all of this is due to an undercount of the increase in the labor input.

These results for MFP indicate that much of the source of improvement over time in standard of living is due to technological improvements in the production of human capital or increased human capital investment. Individuals exposed to more recent education and on-the-job training systems receive more value added to their human capital. This is not captured by composition adjustment. In particular, composition adjustment cannot capture a change in the level of human capital accumulated by college educated workers from the 1966 birth cohort compared to the level accumulated by an otherwise identical individual from the 1946 birth cohort. Similarly, composition adjustment cannot capture the increased human capital for females that would be expected from a large increase in lifetime participation and hours for females.

7 Discussion and Conclusion

For many issues of major policy concern, including growth, wage determination, inequality, and the the productive potential of older workers, it is important to identify human capital prices and quantities separately. Various strands of the current literature often implicitly make extreme and conflicting assumptions to provide identification. For example, the college premium or skill biased technical change literature typically assumes that all of the change in the ratio of relative wages for college graduates compared to high school graduates is due to a change in relative prices and none is due to a change relative quantities. In contrast, life-cycle optimal human capital investment studies often assume a constant price over the life cycle.

In this paper we have taken an explicit identification approach, guided by standard human capital theory, and derived a baseline set of price series for three different types of human capital. We also subjected the baseline series to extensive sensitivity and robustness checks. One of the most interesting results is that the price series are highly correlated over a long time period, from 1963 to 2003. This has important implications for studies of inequality and skill premia. A second robust

[44] See Table PB4a in mfp2ddod.txt at the BLS Multi-factor Productivity website.

result is that there have been strong secular trends in the price. This has important implications for the contribution of human capital to growth and for the interpretation of the life-cycle profiles of human capital.

The credibility and usefulness of the approach was examined in three different contexts. First, in the life-cycle context, the use of the price series shows that the implied sequence of life-cycle human capital profiles for successive birth cohorts from the 1920s to the 1950s all have similar shapes and follow a simple pattern that is consistent with an optimal human capital model of the Ben-Porath type. In contrast, using the standard alternative constant price assumption, the profiles are very different in shape and show a confusing cohort pattern that is hard to interpret. Second, the high correlation between the price series across education groups implies that much of the change in relative wages by skill is due to changes in relative quantities rather than relative prices. Card and Lemieux (2001) showed that the well known observed increase in the college premium was in fact almost all due to the less well known fact that there was a large increase in the premium for some cohorts, but not for others. Examination of the implied changes in relative quantities when the baseline price series are used shows that the pattern of relative quantity changes implies precisely the changing pattern of college premia by age observed by Card and Lemieux. Third, the price series was used to construct a new quality adjusted measure of the labor input. The results suggest that significant growth in efficiency units of labor in the U.S. over the 1975-2001 accounted for most, if not all, of the growth attributed to TFP using conventional input measures.

Human capital is widely recognized as the most important asset that individuals hold. Unfortunately, it is not directly observed. As a result previous research has relied on a variety of proxies based on observable characteristics such as years of schooling. For a variety of purposes, such as within country variation in wages for a given cohort, these proxies can work quite well and have formed the basis of thousands of studies. For issues of secular growth, cross country variation and cross cohort variation in wages, however, they may leave out the most important sources of progress or variation: technological change in human capital production, broadly interpreted, selection effects of changing educational attainment, and the increased life-cycle investment that accompanies the increased labor market attachment of women. Adjusting the labor input for quality changes using the estimated price series greatly reduces the contribution of MFP growth to recent growth in the standard of living in the U.S., and emphasizes the role of increases in the true labor input. This parallels some recent research suggesting that quality adjustment to international comparisons of human capital greatly reduces MFP differences as the source of cross country differences in wealth.[45] A large part of the increase in the quality of the labor input is not due to composition changes but instead to technological change in human capital production and changes in the optimal accumulation over the life-cycle, especially for females. Since most attempts at adjusting the labor input for quality changes, such as Krusell *et. al.* (2000) or the official BLS series used to estimate MFP, only deal with composition, they cannot capture a large part of the quality change.

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A Appendix

The data for the analysis come from the March Current Population Surveys (MCPS). A consistent and annotated version of the files from UNICON was used as the data source. In this Appendix these data are described with particular reference to issues of data quality and comparability over time.

A.1 Consistent Education Categories

The issue of consistency of the education measure arises because of a break in the education questions in 1991. This break is studied in detail in Jaeger (1997) who compared the education answers from the same respondents at different points in their CPS rotation who were asked the old education questions in their earlier rotation and the new questions in their later rotation. Jaeger offers solutions of two types. First is a linearization of the new educational attainment question that approximates the old "highest grade completed". The recommended mapping to construct a consistent "highest grade completed" or "years of schooling" variable is provided in the first and last columns of Jaeger's Table 2. Second, Jaeger considers 4 category matches rather than linearization. These are high school dropouts, 12th grade, some college, and college graduates. The recommended mapping for creating these four categories consistently across time is given in Jaeger's Table 6. In this paper we use the same four categories as Jaeger and follow his category mapping across the break.[46]

A.2 Consistent Annual Hours Measures

The MCPS annual labor incomes are for the year preceding the survey. Prior to the 1976 survey (1975 earnings) reported working hours in the survey could not be related to the previous year's earnings. In the MCPS data, hourly wages can be constructed as the ratio of annual labor income to annual working hours. Annual working hours can be constructed as the product of weeks worked per year and usual hours worked per week for the 1976 survey onward. Prior to this survey year, usual

[46]There is a small difference in this mapping from a standard high school dropout/high school graduate cutoff using the linearization. For the period 1975-1990 this is the same under both sets of coding. However, for the period 1991-2001, in contrast to mapping of code 38 into the less than high school group, Jaeger's category mapping puts them into high school. This is due to the use of the median rather than the mean in Table 2. The mean of the 38 group is actually 11.38 but the median is 12. Up to 1990 the fraction of high school dropouts is the same under both definitions. The cumulative fraction up to and including 11 over the $1985-1990$ period was 17.76, 17.36, 17.31, 16.86, 16.68 and 16.09. Jaeger's category mapping takes it to 13.40 for 1991 and the alternative takes it to 15.12. Further inspection, however, shows that the big drop is actually in the cumulative to 10 years which is common to both measures, so the less drastic drop from the alternative method is not to be preferred on this ground.

weekly working hours were not recorded and weeks worked were reported in grouped categories. An imputation procedure was used to create a series back to the 1964 survey.

- *Hours Worked per Week Last Year.* For the surveys before 1976, the MCPS variable hrslyr ("hours last year") is not available, and an estimate has to be obtained from data on hours. The question for this variable is always the same: "In the weeks that ..... worked, how many hours did ..... usually work per week?" The valid positive codes are 1-99, which corresponded to the number of hours. The question for the hours variable in survey years 1962-1993 was: "How many hours did ..... work LAST WEEK at all jobs?" For 1994 onwards the "hours last week" variable is constructed from two questions: "Last week, how many hours did you actually work at your (main) job?" and "Last week, how many hours did you actually work at your other job(s)?" The valid positive codes for these variables for all the survey years were 1-99, except for 1963-1967 where they were 1-98. An estimate of hours worked per week last year for the survey years prior to 1976 is constructed as follows. First, for the individuals who were working last week, their "hours last week" is used as an estimate of their "hours per week last year." Second, for the individuals who were not working last week but who had worked last year, their "predicted hours last week" is used as an estimate of "hours per week last year" where the predicted hours is obtained from a regression of "hours last week" on age, education in years and a female dummy variable for each year on the sample of those employed in the survey year.

- *Weeks Worked per Year Last Year.* For the 1962-1975 surveys the question is: "In 19XX how many weeks did ..... work either full time or part time (not counting work around the house) ?" For the 1976 and 1977 surveys the question was amended to: "In 19XX how many weeks did ..... work either full time or part time, not counting work around the house? Include paid vacation and paid sick leave." From the 1978 survey on, the question became: "During [19XX/20XX] (last year) in how how many weeks did ..... work even for a few hours? Include paid vacation and paid sick leave." Prior to the 1976 survey this variable was only available in intervals. UNICON created a time consistent variable for "weeks worked last year" by using interpolated values based on interval means from some post-1975 surveys.

A.3 Consistency and Quality Issues for the Annual Earnings Measure

The annual wage and salaries earnings data are from the UNICON time consistent "income from wage and salary" variable derived from the MCPS variable *incwag* (income from wage and salary). The definition from the glossary is as follows:

- Money wages or salary is defined as total money earnings received for work performed as an employee during the income year. It includes wages, salaries, Armed Forces pay, commissions, tips, piece-rate payments and cash bonuses earned, before deductions are made for bonds, pensions, union dues, etc. Earnings for self-employed incorporated businesses are considered wage and salary.

The question for the survey years 1963-1968 is "Last year how much did ..... receive: In wages or salary?" For the survey years 1969-1974, the question was slightly amended to "Last year ($19XX$) how much did ..... receive: In wages or salary before any deductions?" and for survey years 1975-1979 was further amended to "Last year ($19XX$) did ... receive any money in wages and salary? If so, how much did ... receive before any deductions?" From 1980 onwards there are multiple questions for the source so that "income from wage and salary" is a sum of components, but there is a single top-code variable that applies to the to the total. From $1988B$ to 1995 the construction is (*incer1* if *ernsrc=1*) + *incwg1*, where *incer1* is the CPS "income from the longest job", *ernsrc* is 1 if the source of income from the longest job is wage and salary, and *incwg1* is the CPS "income from other wage and salary." There are two top-code flags for this period, one for *incer1*, and one for *incwg1*, hence the "income from wage and salary" variable can have a value above any single top-code cut off value. While the form of the question has been relatively stable over time, several potential quality issues arise from substantial time variation in the incidence and treatment of top-coding, and in allocated values.

For $1963-1987$ the top-coding, if any, takes place on the total "income from wages and salaries" CPS variable *incwag*.[47] There are no top-coding flags before 1975. For $1963-1966$ the highest value of *incwag* is 99900, but there is no apparent top-coding from inspection of the frequencies. For 1967 the highest value is 50000 and there is clear top-coding from the frequencies, though without a flag it is not possible to say which of the observations with value 50000 are top-coded. The same applies for $1968-1974$. For the years 1975 to 1987, top-coding is indicated by a top-coding flag. For

[47] Years refer to earnings year.

1975 − 1980, the highest value is 50000. For 1975 and 1977 − 1980, the top-coding flag and frequency of *incwag* at 50000 agree. For 1976 the flag indicates far too many top-coded and must be incorrect; the frequency at 50000 strongly suggests top-coding at 50000: the conditional frequency of 50000, given that the observation is above 45000, is almost the same as 1975. For 1981 − 1983 the highest value is 75000. It is possible to say which of the observations with value 75000 are top-coded from the top-coding flag; the information from the flag and the frequencies agree. For 1984 − 1987 the highest value is 99999. It is possible to say which of the observations with value 99999 are top-coded from the flag, except for 1984 where the flag must be incorrect.[48]

For 1988 − 1994 the top-coded value for the first component of "income from wages and salaries" , the CPS variable $incer1$ is 99999. It is possible to say which of the observations with value 99999 are top-coded from the flag for this component. This flag has missing values when there is no top-coding for 1988; otherwise the flags are fine. The top-coded value for the second component of "income from wages and salaries", the CPS variable $incwg1$, is also 99999. This is only binding in 1993 and 1994. However, the flags and the top codes disagree in part. The other wage and salary flag has no observations indicating top-coded up to 1992 and a few thereafter. The longest job flag has 611 − 1359 indicating top-coded. Of these, about three quarters are at the top cutoff (99999), and about 10 percent are above, but only infrequently are they double 99999. This is consistent with both flags. However, there remain 10 − 15 percent of those indicated as top-coded on the longest job with values for the total "income from wages and salary" of zero. This is inconsistent with the flags. The distribution above 90000 shows that most of the observations above the 99999 cut off are top-coded from the longest job, but a small number are above because neither the longest job, or other wage and salary are individually top-coded but their sum exceeds 99999. The details are as follows:

Year	wg1flag	ern1flag	mode > 90000	zeros *incwag*	199998s *incwag*
1988	0	611	99,999	110	0
1989	0	896 (1.08pc)	99,999	186	2
1990	0	864 (1.05pc)	99,999	168	0
1991	0	873 (1.08pc)	99,999	151	1
1992	0	980 (1.23pc)	99,999	141	0
1993	18	1180 (1.53pc)	99,999	176	6
1994	29	1359 (1.77pc)	99,999	158	11

[48] For 1984 the flag must be incorrect; the frequency at 99999 strongly suggests top-coding at 99999 since the conditional frequency of 99999, given $> 70,000$ in 1984 is almost the same as 1985. For 1985 − 1987 the flag and frequency of *incwag* at 99999 agree.

Beginning in the survey year 1996 - earnings year 1995 - a new method was used to top-code the two components. The Unicon codebook describes this as follows: "Individuals with values above the top-code are grouped by sex, race/origin, and worker status. A mean income value is calculated within these groups and assigned to the individuals. Therefore, the largest values observed for these variables are greater than the top-code values. Replacement values for 1998 are detailed in Appendix H.3." (Unicon: Appendix H). In addition, beginning with the earnings year 1995, the top-coded value was raised to 150000 on the first component, $incer1$, and lowered to 25000 on the second component, $incwg1$. Examination of the distribution of the UNICON total "income from wages and salaries" above 149000 shows the following:

Year	wg1flag	ern1flag	mode > 149000	mean > 149000
1995	309 (0.46)	406 (0.60)	302539 (53.72pc)	274620.6
1996	227 (0.33)	490 (0.72)	318982 (59.55pc)	296586.4
1997	445 (.065)	546 (0.79)	330659 (52.71pc)	296775.1
1998	428 (0.62)	576 (0.83)	306731 (54.08pc)	297244.1
1999	68719 (96.80)	63568 (89.55)	229339 (57.91pc)	219548.8
2000	577 (0.84)	730 (1.07)	335115 (58.91pc)	294638.7
2001	851 (0.76)	1408 (1.25)	320718 (56.15pc)	292384.1

Clearly, something is wrong with 1999. The Unicon Appendix H4 indicates the top-code variables are inconsistent. The distributions of "income from wages and salaries" above 149,000 show mass points in the 2000 distribution that correspond to the replacement values given in Appendix H for that year. There are similar mass points in the 1999 distribution. It might be possible to infer substitute replacement values from adjacent years.

Allocated values are a serious issue in CPS data because in some years as many as 25 percent of the values may be allocated. For overall total earnings calculations, the complex top-coding and allocated value issues present some problems, but they are not too serious because of the relatively small incidence of top-coding in most years, and the tendency of the allocated values to be reasonably close to averages over fairly large groups. However, for calculating the price series, using much smaller totals, including a group such as 53-62 year old highly educated workers, the incidence can be a lot larger and the top-coding issues more of a problem.[49] The strategy adopted to minimize these problems was to use medians where possible, and to flag any of the cases where top-coded

[49] Bollinger and Hirsch (2008) recently drew attention to the serious problem of proxy responses and allocated values in Current Population Survey data. For some years, up to one quarter of the observations on earnings may be allocated values. Hirsch and Schumacher (2004) document a dramatic example of how very misleading results can be obtained without careful treatment of the allocated values

values were included in the calculation. The calculations were then performed with and without the top-coded and allocated observations to assess the likely magnitude of any biases. Biases could be very large when raw wages are used, as illustrated in Figure A1 where an outlier in the MCPS data turns out to be one of the mean income replacement values assigned to a top coded observation. The use of medians obviates the need for trimming. However, for comparison with log wage series some modest trimming was examined. Figure A2 shows that, except for the pre-1975 period, where more outliers may be expected due to the potential mis-measurement of “hours per week last year”, the trimming makes almost no difference.

A.4 Issues with the Standard Unit Sample

The standard unit sample is all males with the education measure corresponding to high school dropouts. The series can be derived from average wages, median wages or average log wages. There is a choice of what minimum hours restriction to impose and how allocated or top-coded values should be treated. There is a choice of trimming level if any. Top-coding is not present in the standard unit sample until 1995. In 1995 and 1998 one observation is top-coded. In 2001, 4 observations are top-coded and in 2002, one observation is top-coded. Allocation, however, is more of a problem. It ranges from 8-27 percent. Figures 3a and 3b show that the series are not very sensitive to the treatment of allocated values or hours restrictions.

In constructing the standard unit sample one must decide when to take the measure of completed education. Checks on the frequency distribution for experience by schooling group shows that if individuals under 19 are included, the contemporaneously measured schooling completed for the lowest schooling group is not the correct final frequency - i.e. many go on to more education. By 19-20, however, those contemporaneously reporting a completed level of high school dropout correspond closely to the fraction that would report that same level at later ages. Thus, estimates using the standard unit method should be restricted to samples aged 19 and above. The baseline age group used in the paper is 20-25. Figure A3 shows a very similar pattern for an older age group of 21-27. Even the narrow 19-21 age group, with a relatively small sample and on the borderline of satisfying the completed education requirement and a permanent transition to the labor force, shows a similar pattern.

TABLE 1
BLS and Jorgenson Composition Adjusted Labor Input Series, 1977-2000

	Total Hours (billions)		Composition Adjustment		Labor Input		
	Jorgenson	BLS	Jorgenson	BLS	Jorgenson	Jorgenson*	BLS
1977	145.3967	127.413	0.909	0.902	132.129	114.984	114.984
1978	152.4866	133.839	0.91	0.904	138.723	120.752	120.926
1979	157.8711	138.333	0.911	0.901	143.778	125.091	124.597
1980	156.109	137.054	0.909	0.904	141.864	123.453	123.831
1981	157.1794	138.051	0.917	0.91	144.082	125.322	125.645
1982	153.9752	134.803	0.923	0.919	142.061	123.611	123.948
1983	156.7416	137.183	0.924	0.923	144.768	126.022	126.669
1984	165.4984	145.238	0.933	0.924	154.332	134.238	134.262
1985	169.1046	148.597	0.935	0.927	158.03	137.457	137.7
1986	169.9429	149.594	0.936	0.931	158.982	138.357	139.293
1987	175.6338	154.034	0.941	0.934	165.35	143.807	143.802
1988	180.7782	158.274	0.945	0.941	170.91	148.689	148.93
1989	186.0455	162.533	0.949	0.945	176.628	153.695	153.618
1990	187.2754	161.648	0.958	0.95	179.465	156.175	153.567
1991	183.2378	157.851	0.961	0.961	176.141	153.295	151.664
1992	183.5965	157.69	0.967	0.973	177.577	154.492	153.365
1993	188.5939	162.105	0.976	0.975	184.093	160.263	158.021
1994	194.2605	168.309	0.981	0.98	190.587	165.891	164.937
1995	199.4712	172.948	0.983	0.981	196.095	170.647	169.634
1996	202.7156	175.828	0.991	0.985	200.891	174.805	173.211
1997	209.1744	181.831	0.992	0.991	207.499	180.54	180.116
1998	215.2336	185.709	0.995	0.993	214.15	186.268	184.463
1999	219.4094	189.814	0.997	1	218.739	190.387	189.721
2000	223.0287	191.66	1	1	223.011	194.016	191.66

*Scaled to the BLS series 1977 initial value.

TABLE 2
Comparison of Alternative Labor Input Series, Private Sector: 1977-2000

	Unadjusted Hours		Composition Adjusted Hours	Efficiency Units
	Total (billions)	Index	(Tornqvist)	
1977	117.7537	108.0142	107.8179	110.4726
1978	123.1152	112.9323	112.7404	116.1702
1979	125.6677	115.2737	114.6705	119.2647
1980	129.668	118.9431	118.661	123.3571
1981	131.0276	120.1902	120.711	126.0379
1982	129.3289	118.6321	120.1273	125.5602
1983	132.8805	121.89	123.5739	125.2777
1984	140.7109	129.0726	131.5091	134.1668
1985	146.9159	134.7644	138.4073	143.9580
1986	150.8217	138.3472	142.724	145.9538
1987	154.1638	141.4129	146.1551	154.3805
1988	157.853	144.797	150.7242	161.2959
1989	160.5897	147.3073	154.4506	166.2733
1990	161.7545	148.3758	156.256	167.7117
1991	162.2436	148.8244	158.1804	172.1400
1992	162.7781	149.3147	160.9345	175.0304
1993	165.7894	152.077	165.2209	183.2703
1994	171.3907	157.2149	172.2097	188.0046
1995	177.688	162.9913	178.8962	197.0622
1996	180.9425	165.9767	183.1756	209.4596
1997	185.6065	170.255	188.9621	220.4723
1998	190.6858	174.9142	196.1496	227.2211
1999	193.1994	177.2199	200.1184	231.8148
2000	197.5009	181.1655	205.178	241.3575

TABLE 3
Comparison of Alternative Labor Input Series, Paid Workers: 1977-2000

	Unadjusted Hours		Composition Adjusted Hours	Efficiency Units
	Total	Index	(Tornqvist)	
1977	146.2455	106.5429	106.5563	108.7873
1978	152.5765	111.1551	111.1707	113.7151
1979	155.6163	113.3697	113.3093	116.5053
1980	160.1237	116.6534	116.8424	120.0087
1981	161.009	117.2984	118.1511	122.0738
1982	158.9353	115.7877	117.4353	121.6832
1983	163.7512	119.2961	121.3482	122.0970
1984	172.2239	125.4687	128.1364	130.2097
1985	178.1313	129.7723	133.1505	138.3485
1986	182.9356	133.2724	137.3454	140.5068
1987	187.0298	136.2551	140.737	148.5386
1988	191.5991	139.5839	145.2336	155.3343
1989	195.0625	142.1071	148.6597	160.6502
1990	195.785	142.6334	149.7317	162.0145
1991	197.1212	143.6069	152.1546	167.3767
1992	198.7658	144.805	155.289	170.7903
1993	202.3861	147.4425	159.1748	179.0947
1994	208.1018	151.6065	165.1147	182.4804
1995	213.127	155.2675	169.105	188.8380
1996	215.9565	157.3288	171.8405	198.1814
1997	221.2122	161.1577	177.0715	208.1371
1998	227.0704	165.4255	183.4849	213.6505
1999	231.0326	168.3121	187.553	218.9320
2000	235.3721	171.4735	191.6503	226.2895

TABLE 4
Comparison of the Growth Rates of Alternative U.S. Labor Input Series: Percentage Change 1977-2000

	Paid Workers 20-64		Private Sector Paid Workers 20-64	
EUS	108.01		118.48	
Hours	60.94		67.72	
BLS	79.86		90.3	
	Males	Females	Males	Females
EUS	80.66	180.99	90.35	202.98
Hours	42.75	90.98	49.5	100.1
BLS (A)	56.21	142.93	65.78	163.93
BLS (B)	63.24	122.01	73.81	137.68

TABLE 5
Growth Rates of Fixed Weight Labor Input Series for the United States: 1977-2000

	Paid Workers 20-64	
Efficiency Units	108.01	
Hours	60.94	
BLS	79.86	
Fixed Weight	80.21	
	Skilled	Unskilled
Efficiency Units	244.62	58.47
Hours	145.82	40.16
Fixed Weight	152.65	50.77

Figure 1

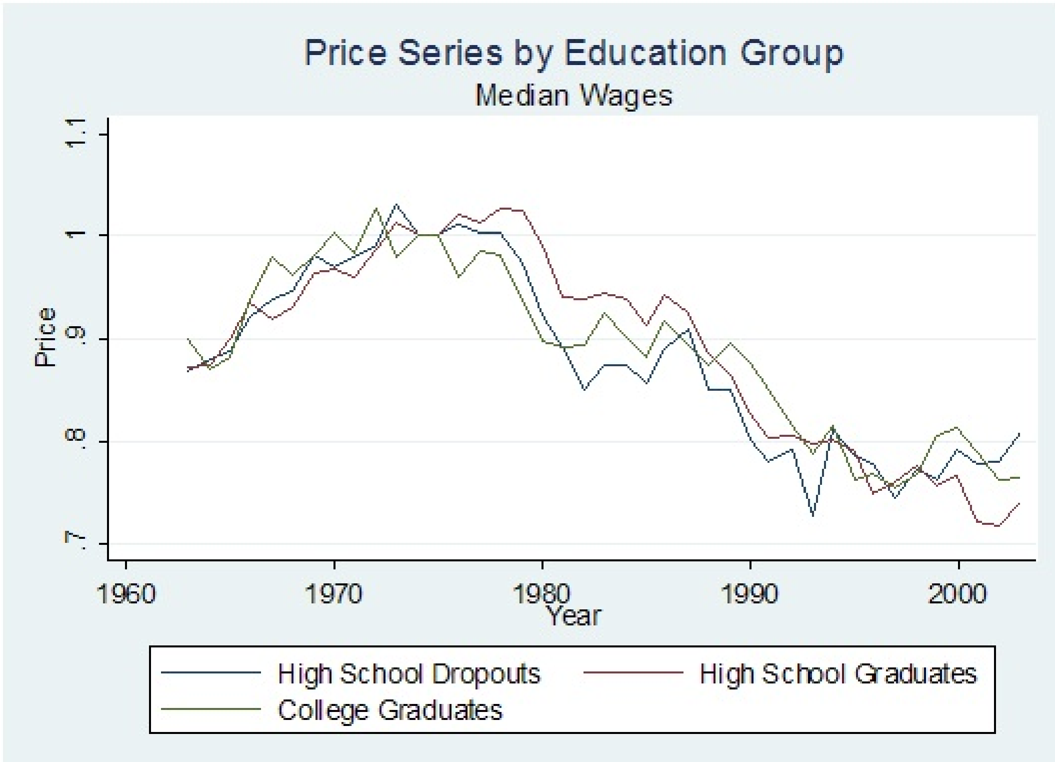


Figure 2

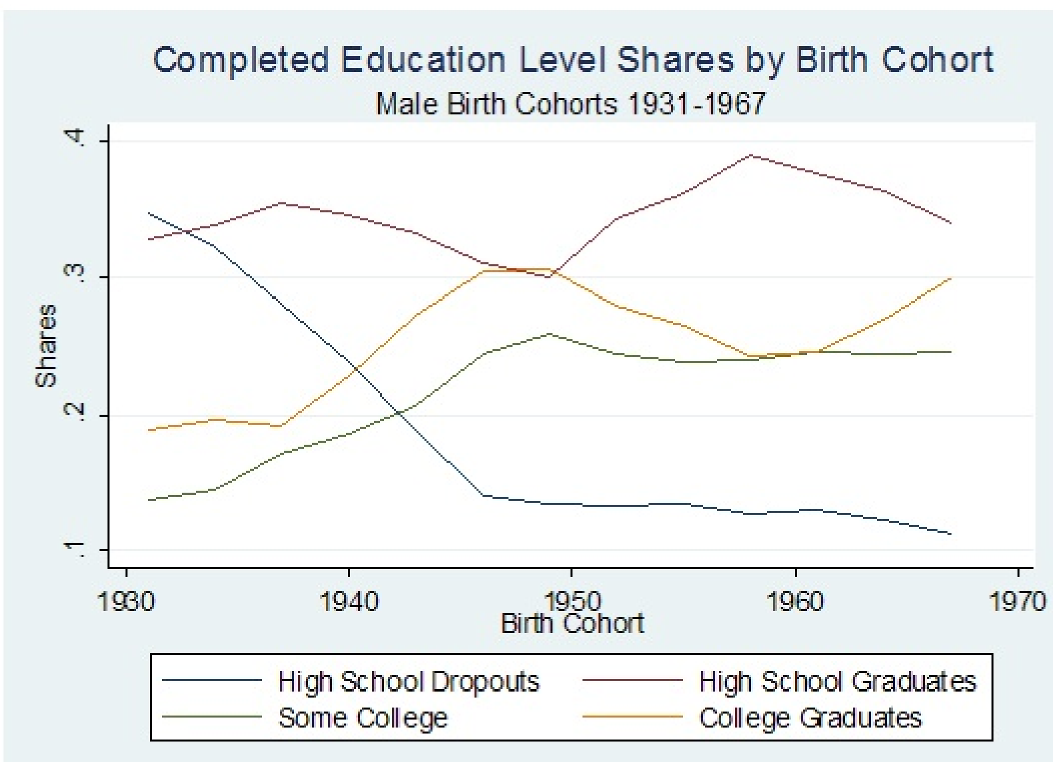
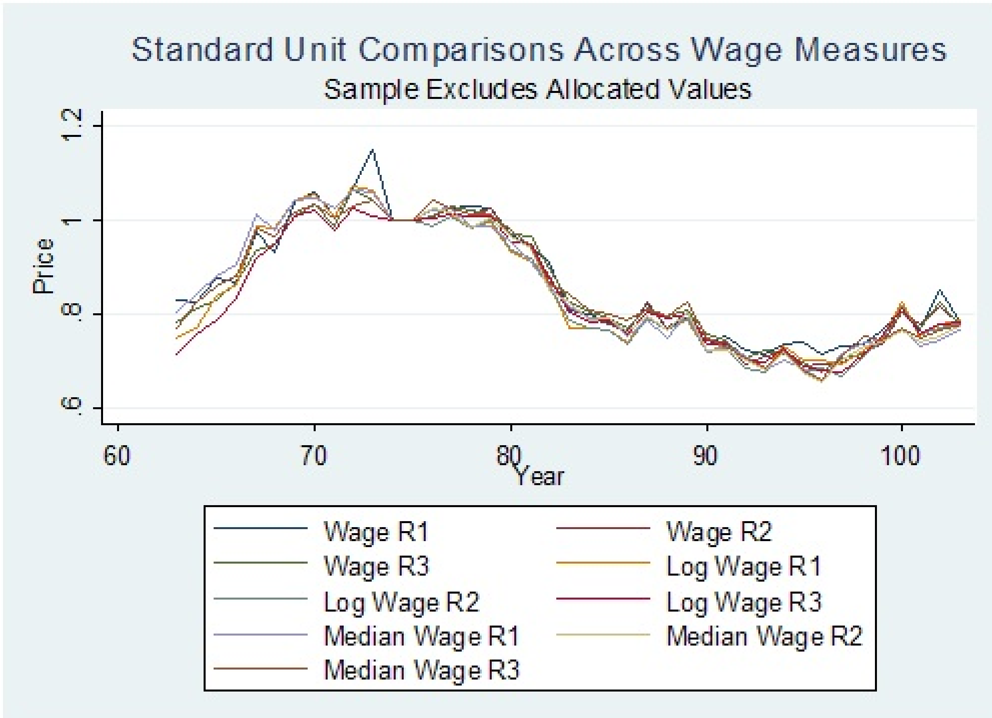


Figure 3



Notes: Sample restrictions as follows: Total annual hours at least 50 (R1); hours per week greater than 20 and weeks per year greater than 10 (R2); hours per week greater than 20 and weeks per year greater than 20 (R3).

Figure 4

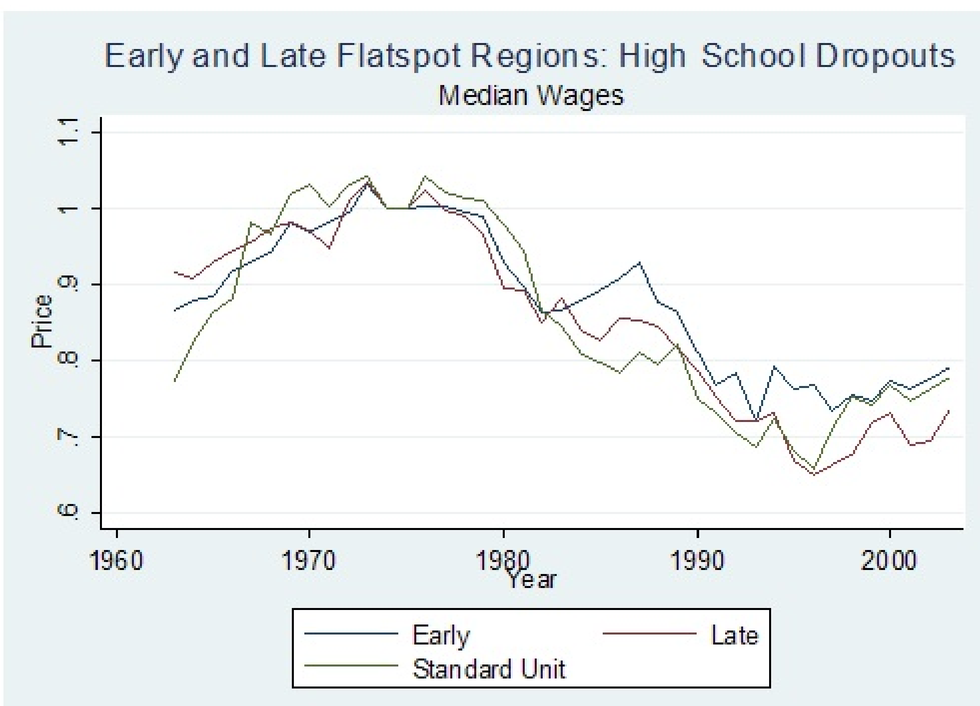
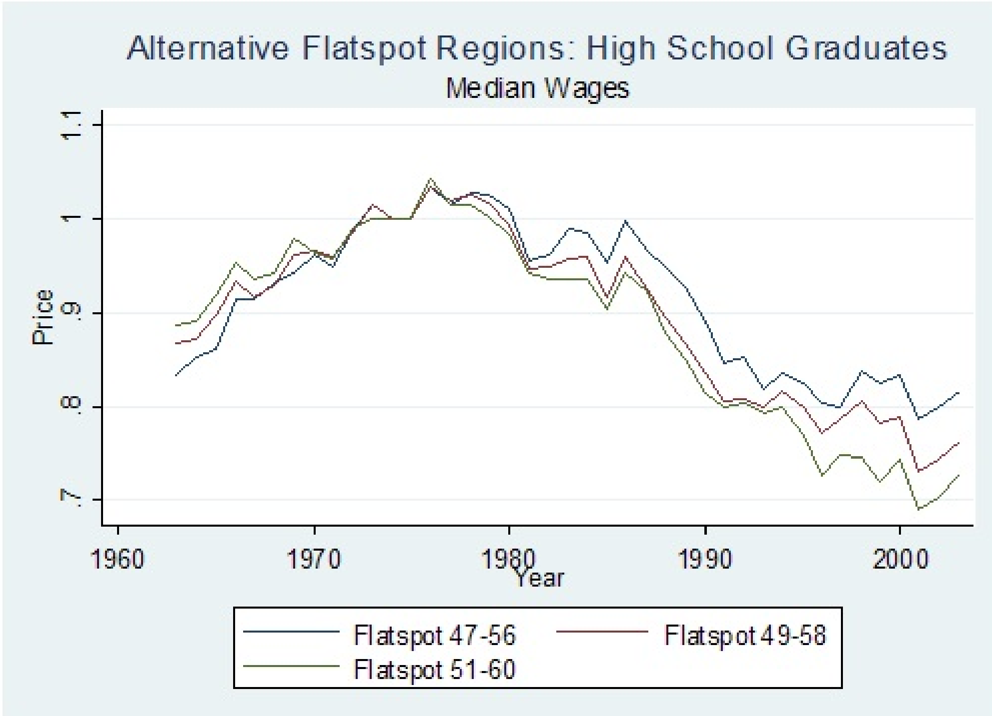


Figure 5



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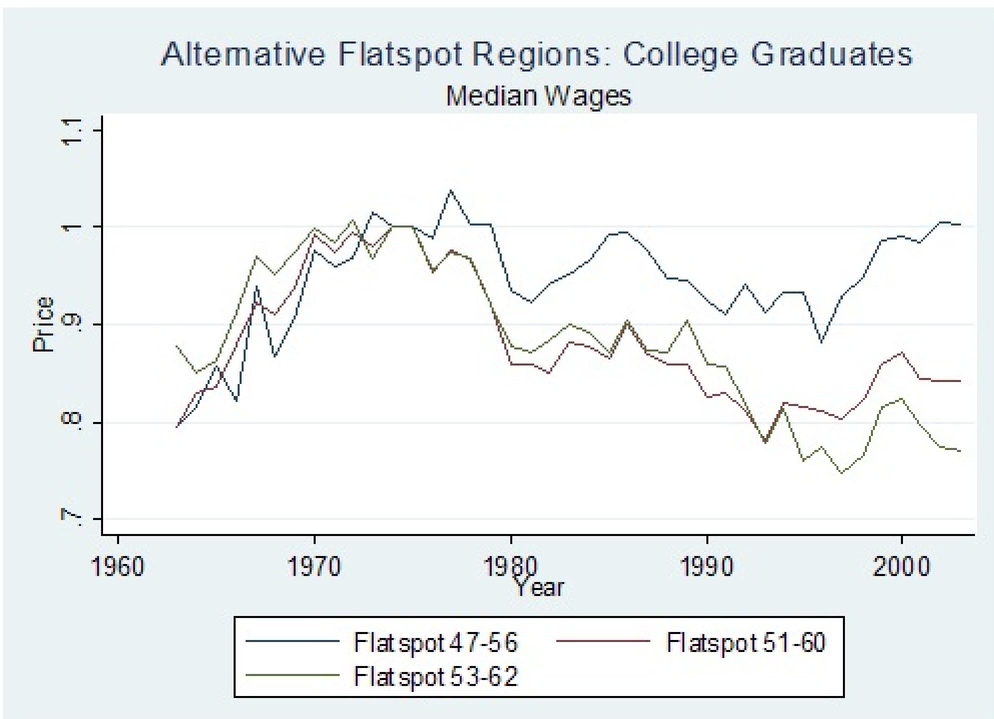


Figure 7a

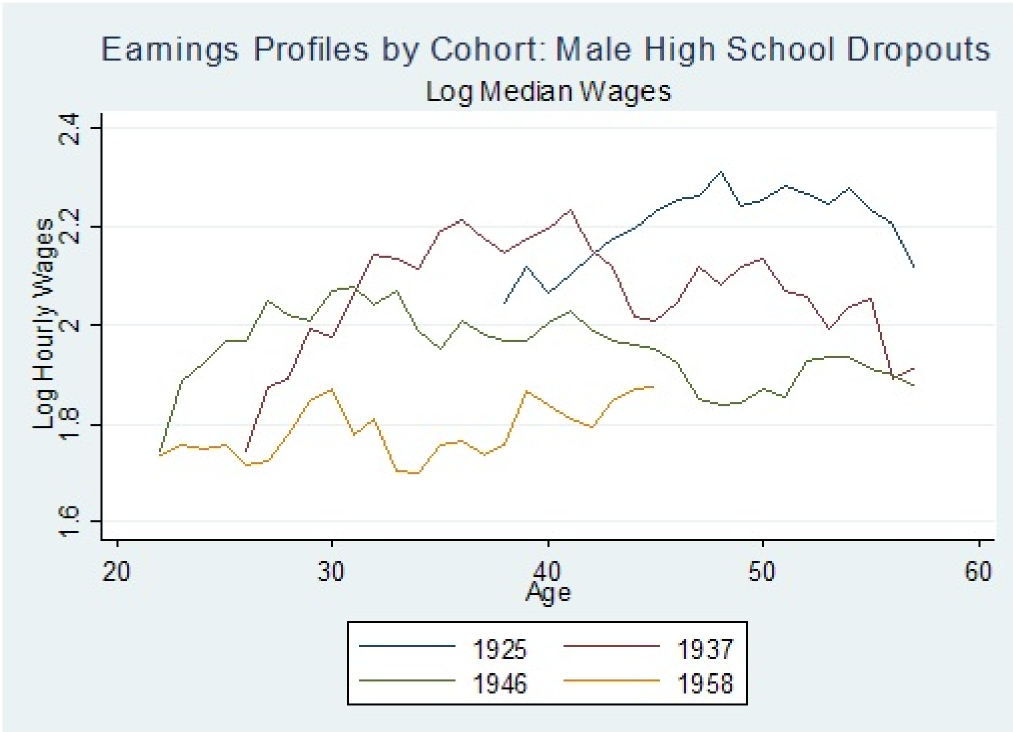


Figure 7b

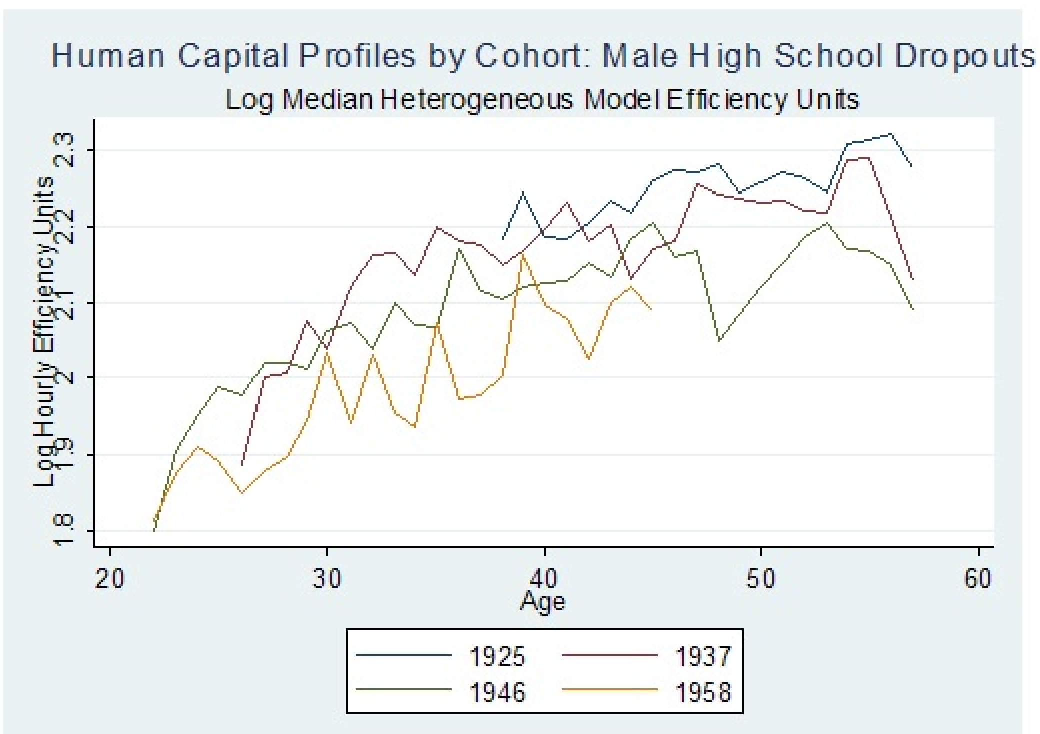
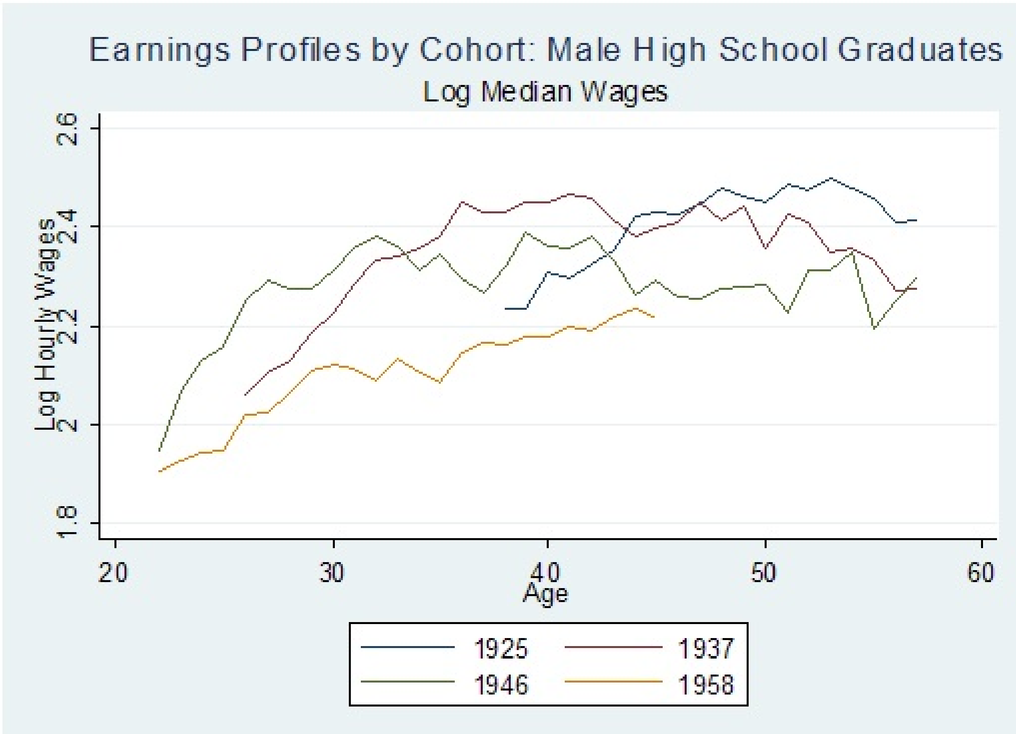


Figure 8a



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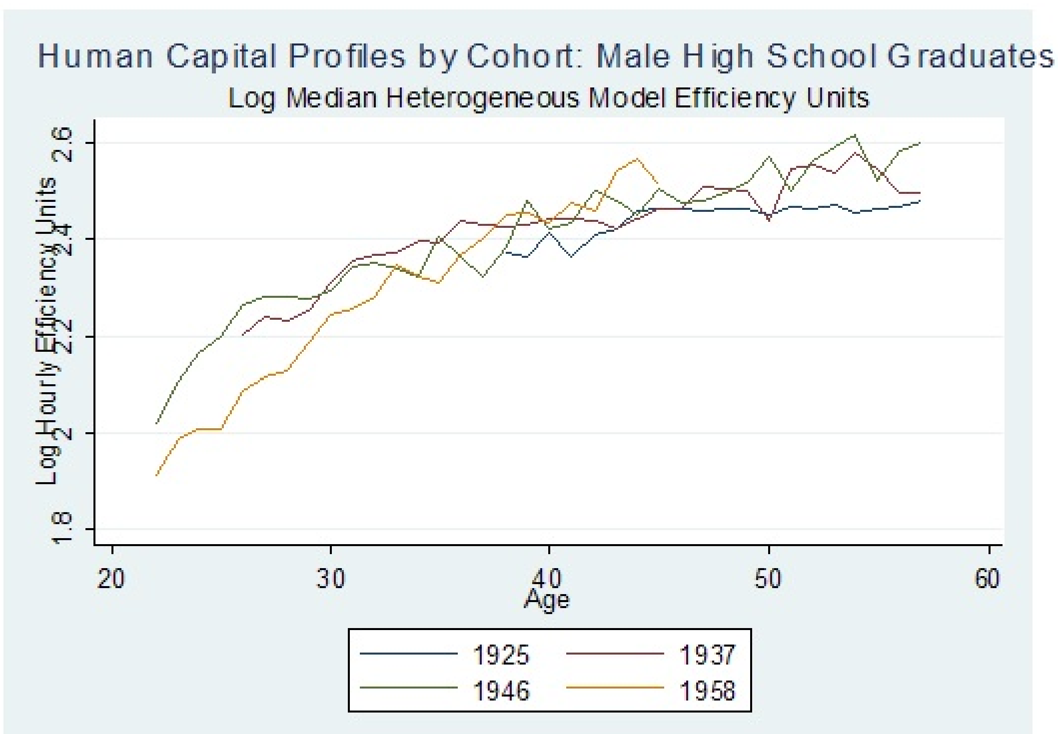

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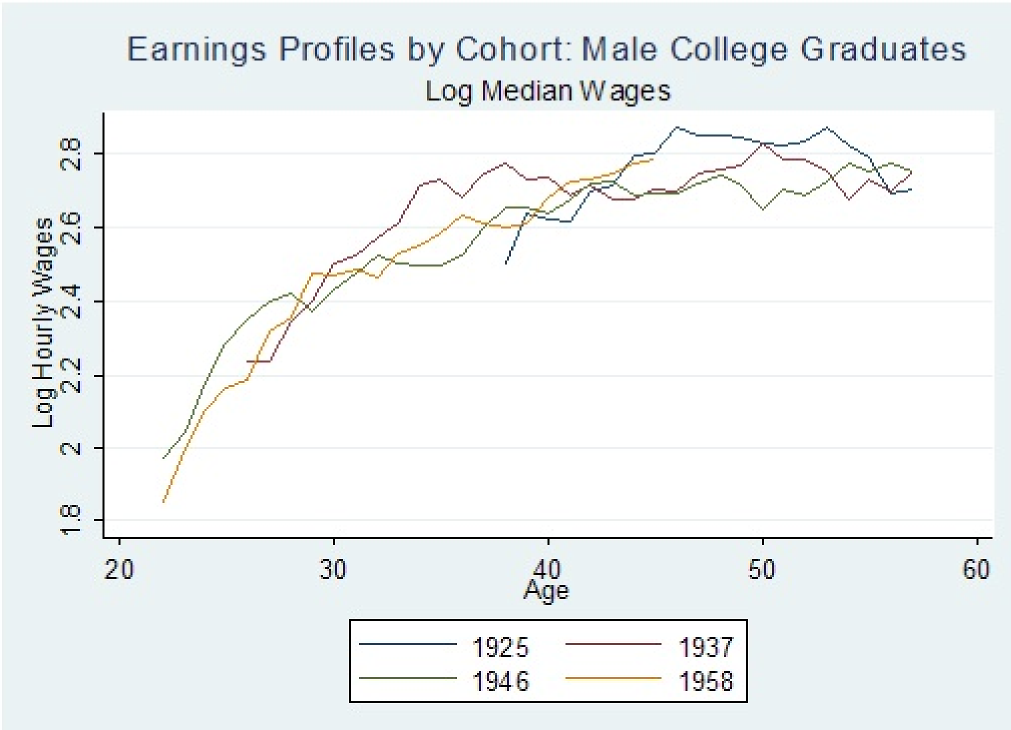

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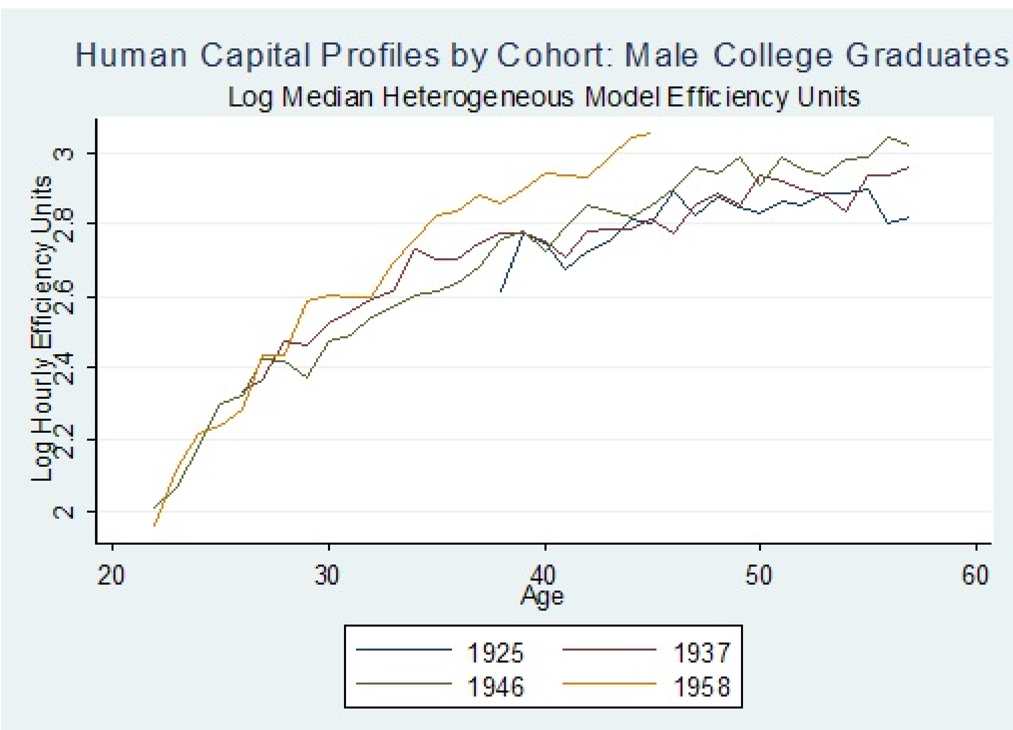

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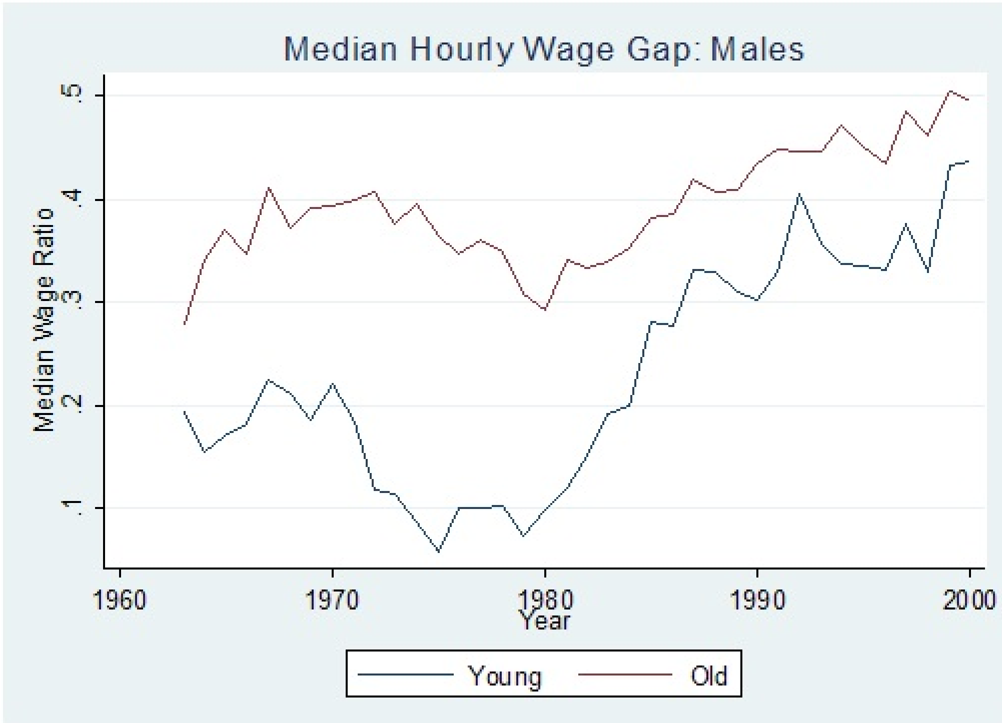

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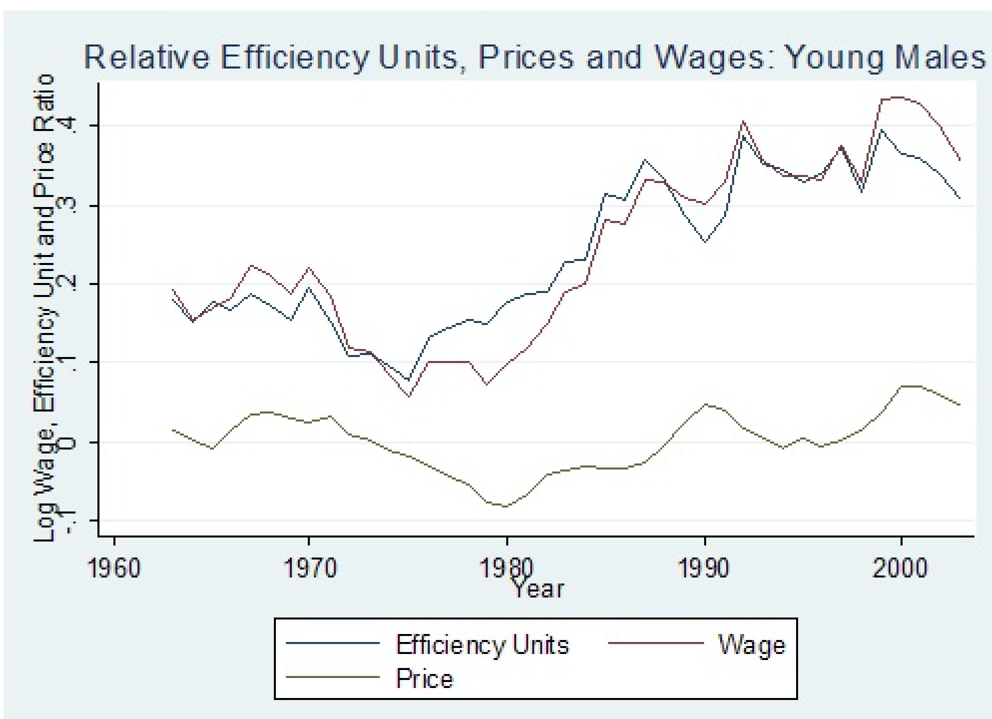
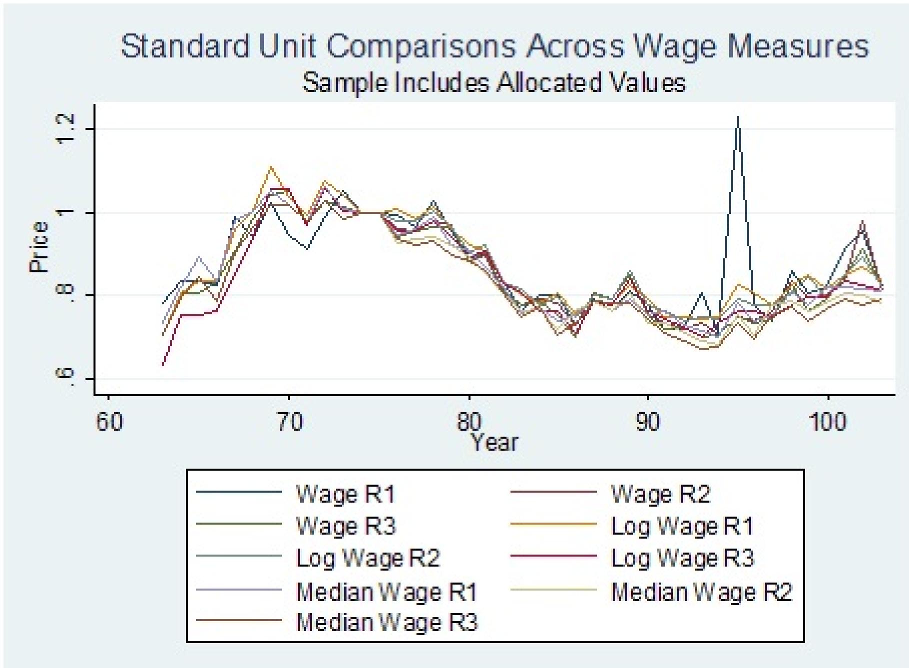
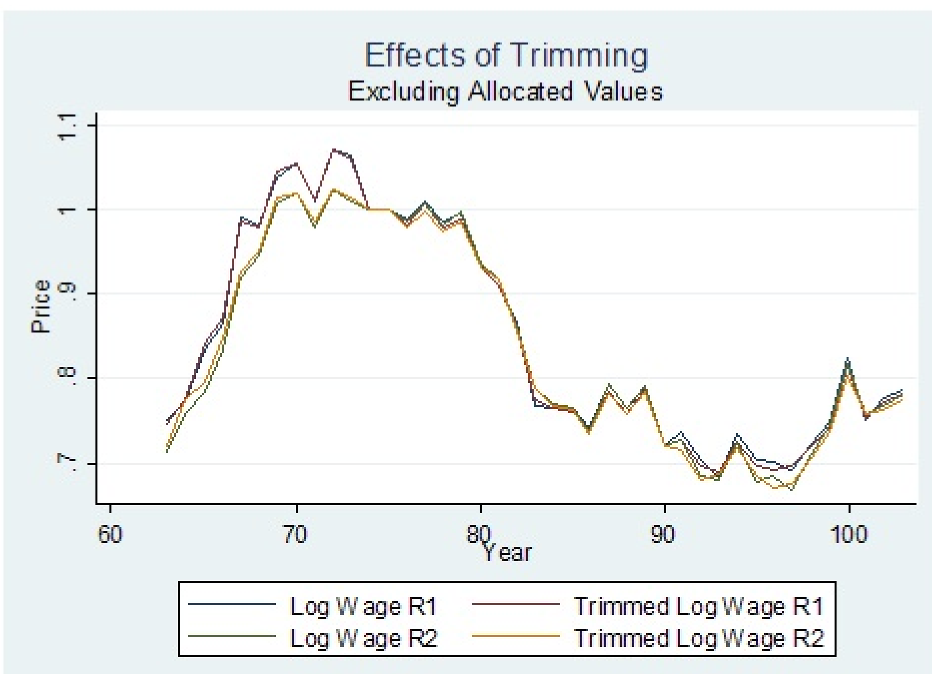


Figure A1



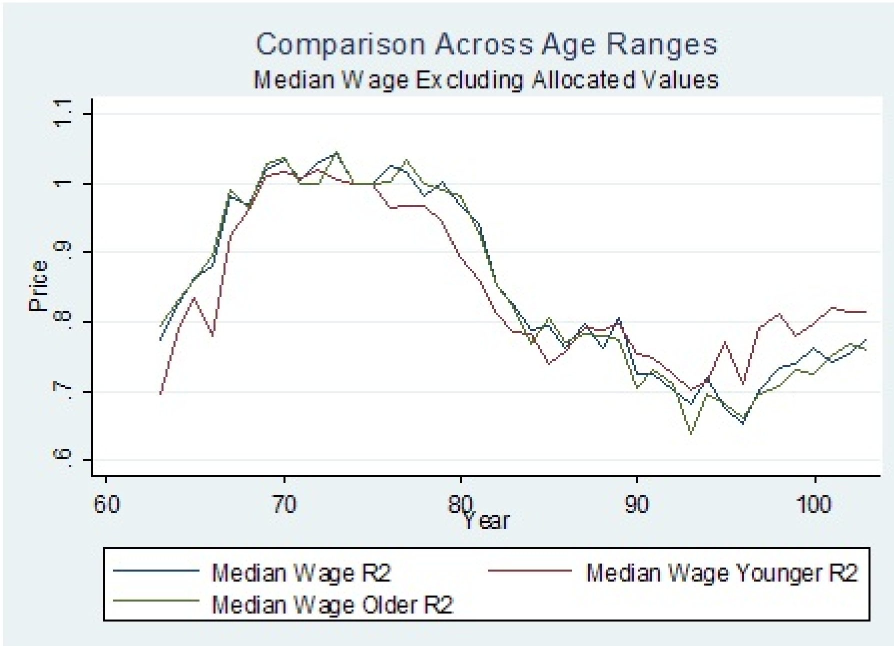
Notes: Sample restrictions as follows: Total annual hours at least 50 (R1); hours per week greater than 20 and weeks per year greater than 10 (R2); hours per week greater than 20 and weeks per year greater than 20 (R3).

Figure A2



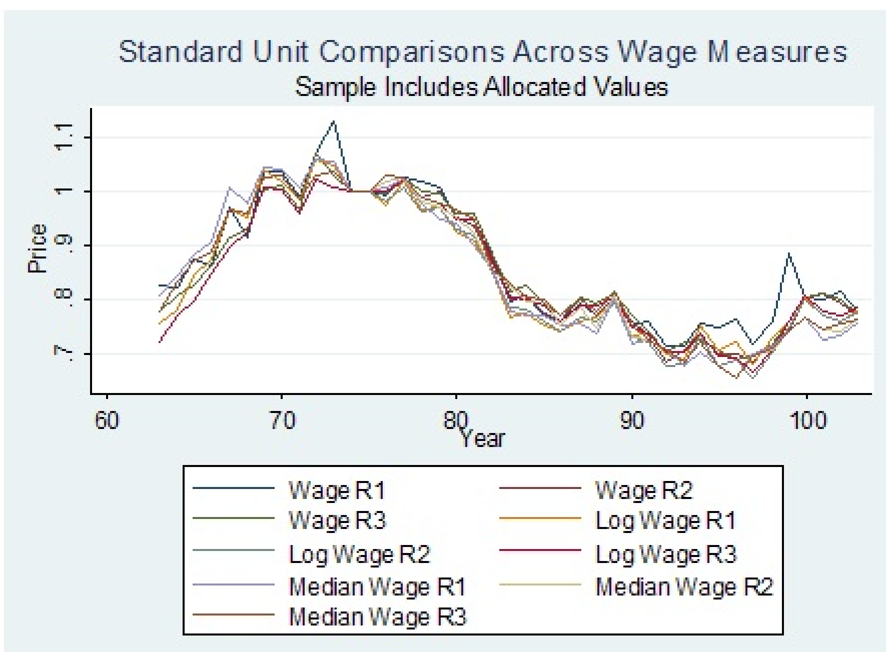
Notes: Sample restrictions as follows: Total annual hours at least 50 (R1); hours per week greater than 20 and weeks per year greater than 10 (R2); hours per week greater than 20 and weeks per year greater than 20 (R3).

Figure A3



Notes: Sample restrictions as follows: Total annual hours at least 50 (R1); hours per week greater than 20 and weeks per year greater than 10 (R2); hours per week greater than 20 and weeks per year greater than 20 (R3).

Figure A4



Notes: Sample restrictions as follows: Total annual hours at least 50 (R1); hours per week greater than 20 and weeks per year greater than 10 (R2); hours per week greater than 20 and weeks per year greater than 20 (R3).