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Barbara M. Fraumeni
Central University of Finance and Economics
Barbara_Fraumeni@hotmail.com

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Barbara M. Fraumeni

Central University of Finance and Economics, Beijing, China
Center for Economics, Finance, and Management Studies, Changsha, China
University of Southern Maine, Portland, ME, USA
National Bureau of Economic Research, Cambridge, MA, USA and
IZA Institute for Labor Economics, Bonn, Germany

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The genesis of this paper came from an interest in including human capital stocks in a production model, followed by a concern about mismatches, accounting identity violations, and inconsistent treatment of inputs. These considerations led to a decision to recommend age and vintage efficiency adjustment of hours.

Production models can take a variety of forms, but frequently there is a mismatch between inputs or between inputs and output or an inconsistency in treatment between inputs, which impacts on productivity estimates, as well as sometimes an accounting identity problem. This potential mismatch was recognized in Fraumeni (2018). Typically, in a value-added production model, GDP is the output measure. Inputs take a variety of forms. Capital is often represented by capital stock, but sometimes by capital service flows with an index based on nominal capital input and the quantity of capital stock. Labor is often represented by the number of workers or by those in the labor force, but sometimes by labor services flows with an index based on nominal earnings and hours worked. These input choices are often dictated by the available data, however, mixing stocks with flows creates a mismatch in most cases, which is a concern if researchers want to estimate productivity. GDP is a flow, capital stocks are a stock as are the number of workers or those in the labor force who can continue to work in the future in the same way that a building can be used in the future. Flows are the output or input to a production process over a set period (say a year); stocks are the input to a production process over a longer period of time (say several years). In addition to the mismatch created when flows and stocks are used in a production model, the basic accounting identity that the sum of nominal inputs must equal the nominal value of output is sometimes not maintained. There seemingly is an inconsistency when physical stocks are adjusted for efficiency as these assets age, but hours worked are not as workers age.[1] Although there may well be a correlation between stocks and flows and efficiency-adjusted physical stocks and different forms of labor input as represented in an econometric model, the underlying premise of a production model is violated with a mismatch or an inconsistency.

Interest in this mismatch and inconsistency arose from a desire to measure human capital productivity or total factor productivity (TFP) when human capital is a stock, such as that in Jorgenson-Fraumeni (J-F). The term "human capital" is applied in a variety of research contexts. Sometimes when education is a component of a production model, when entered separately or as a composition or quality adjustment to labor input, the term is used. In this paper, the term human capital refers only to a measure that has current and future flows as a physical capital stock does, for example from structures or equipment. This definition allows a focus on productivity estimation highlighting stock and flow mismatches and physical stock and hours inconsistencies, and discussing the measurement problems, exacerbated by lack of information, associated with vintage effects.

There are four conclusions of the experimental methodological investigations in this paper. The first is that hours should be efficiency age-adjusted and such adjusted hours can be useful to help identify vintage effects. The question is whether an hours adjustment should be applied to current hours or to lifetime hours, or to both. The second conclusion is that more research is needed to identify different types of efficiency effects, particularly how to include these effects in production models that estimate TFP. The third conclusion is that a labor input index of current hours, adjusted or not, should be the labor input measure in such a production model

[1] In this paper, the term physical stocks refers to physical and intangible stocks, the latter such as R&D.

rather than an index of Fraumeni lifetime hours human capital stock or J-F human capital lifetime income stock, to avoid a greater likelihood of a violation of the requirement that the quality of these hours be constant over time, notably to avoid problems with unrecognized future vintage effects. However, in the context of future sustainability the best human capital companion measure to a production model with current hours and TFP is a Fraumeni lifetime hours human capital stock. The last conclusion is that much more research is needed to update and refine the efficiency adjustments of physical capital stock. Many service lives and the shape of their age-efficiency functions are dated, and rarely differ by vintage; this probably impacts on all methodologies whether they be geometric (e.g., the US Bureau of Economic Analysis) or hyperbolic (e.g., the Australian Bureau of Statistics and the U.S. Bureau of Labor Statistics form of the hyperbolic function).

TFP results in this paper are only suggestive because of potential issues with the underlying data, but is hoped that a consistent data base can be constructed by someone in the future to estimate TFP. However, the categories of over time U.S. data will be at a less than the most detailed level available because of issues with representativeness.

Vintage effects are estimated using two different methodologies, one based on research by Bowlus and Robinson (2012) and Inklaar and Papakonstantinou (2020) and the other employing quality indexes constructed with Törnqvist indexes. The results differ significantly. It is impossible in the context of this paper to determine if this is because of the methodology or the differences in the data sets.

Much future empirical work is needed.

Cobb-Douglas Production Models

A Cobb-Douglas production function is commonly used in research, particularly when a large number of countries are being compared. Casselli (2005), Hall and Jones (1999), and Mankiw, Romer, and Weil (1992) are frequently cited.

Casselli modifies the Hall and Jones production model. Casselli's basic production function is:

Equation (1) $Y=AK^{\alpha}(Lh)^{1-\alpha}$,

where Y is GDP, A is the efficiency or TFP factor, K is the aggregate capital stock, and (Lh) is the quality adjusted labor input. Barro-Lee (2013 and barrolee.com) is the source for the quality adjusted labor input component which is set equal to the average educational attainment of those aged 25 and over.

Mankiw, Romer and Weil begin with a standard Solow (1956, 1959) Cobb-Douglas model. They conclude that steady state income per capita can be represented by:

Equation (2) $Y/L=\ln(A(0))+gt+(\alpha/(1-\alpha))\ln(s)-(\alpha/(1-\alpha))\ln(n+g+\delta)$,

where Y is GDP, L is the working age population aged 15-64, A(0) is the technical change term, s is that average share of real investment in real GDP, g is the rate of growth of technical change, n is the rate of growth of L, and δ is the rate of depreciation. In this model, although investment in the share is a flow, it is not equal to the capital input (capital service flow) into production. However, this formulation is consistent with the purpose of their model as they are explaining income per capita rather than indicating how inputs produce output.

Jones (2014) concentrated on the skill levels of workers. He modifies a labor augmenting Cobb-Douglass production function:

Equation (3) $Y = K^{\alpha} (ALH)^{1-\alpha}$,

by using a different aggregator for H, which he calls the Generalized Division of Labor (GDL) aggregator:

Equation (4) $H = [h_1^{(\theta-1)/\theta} + Z(H_2, H_3, \ldots, H_N)^{(\theta-1)/\theta}]^{\theta/(\theta-1)}$

where θ is the elasticity of substitution between unskilled human capital, H_1, and an aggregation of all other human capital types, $Z(H_2, H_3, \ldots, H_N)$. The GDL does not require that a specific type of aggregator be specified or that the underlying quality of labor be known. As such, it is an ideal aggregator to investigate income differences between countries, for example rich and poor countries as Jones did, but it is not intended to describe production within a country with labor input flows.

In a sources of economic growth analysis production models by Jorgenson and his co-authors, which Jones labels traditional accounting, output and labor and intermediate inputs are measured with flows, with the exception of physical capital input which is measured by a stock index.[2] Contributions to output growth are determined by Törnqvist input indexes; output is also measured with a Törnqvist index.[3]

Jorgenson-Fraumeni Human Capital

J-F human capital is a stock, represented by the lifetime income of individuals discounted to the present and allowed to grow at a specific rate. The early human capital papers which established the methodology were co-authored by Jorgenson and Fraumeni (1989, 1992a, 1992b); subsequently publications were co-authored by Christian (2016), Fraumeni and Christian (2019),

[2] See for example chapter 9 of Jorgenson, Gollop, and Fraumeni (1987).
[3] Jorgenson prefers the term translog to the term Törnqvist to describe the same index.

and Fraumeni, Christian, and Samuels (2017, 2021). Quality in J-F by category is the ratio of a Törnqvist human capital quantity index to a simple (unweighted) summation of the corresponding population. The growth rate of a Törnqvist human capital quantity index is a summation of weighted logarithmic growth rates of population, where the weights are average nominal shares of nominal lifetime human capital service flows. The qualities vary by type of human capital stock and transform population into a quantity of human capital services.[4] Because the flow of human capital services is proportional to the human capital stock as long as the quality of human capital is constant over time, the Törnqvist human capital quantity index can represent the flow of human capital services in a Jorgenson production model. Similarly, because the flow of physical capital services is proportional to the physical capital stock as long as the quality of physical capital is constant over time, the Törnqvist human capital quantity index can represent the flow of physical capital services in a Jorgenson production model. [5] However, there is a different type of mismatch between output and inputs even if the analysis is restricted to market human capital as the logarithmic rate of growth is weighted by average lifetime income shares in the construction of human capital investment output and labor input, which both include current and future earnings, whereas other than human capital output, e.g., physical capital input, and labor input, include only current output or input.

The following describes how J-F human capital is constructed as the next section presents results from a production model with capital, labor, and J-F human capital inputs and TFP.

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[4] See p. 130-31 of Jorgenson, Gollop, and Fraumeni (1987).

[5] See p. 130-31 of Jorgenson, Gollop, and Fraumeni (1987). The principle described on these pages for physical capital stocks applies equally as well to human capital stocks. In Cobb-Douglas and other models which include physical capital stocks as a measure of capital input or employees (instead of hours) as a measure of labor input, unless a proportionality assumption is made, there is a flow/stock mismatch.

In the J-F formulation, from age 15 through 34, individuals may work at the same time as going to school. From age 35, only work is possible.

Nominal market human capital stock measures, per capita human capital in year y for a person of sex s, age a, and years of education e for those who might attend school and engage in market work is equal to:[6]

Equation (1) $i_{y,s,a,e} = ymi_{y,s,a,e} + (1+\rho)^{-1}(1+g)sr_{y,s,a+1}[senr_{y,s,a,e}i_{y,s,a+1,e+1} + (1 - senr_{y,s,a,e})i_{y,s,a+1,e}]$

where

s = sex (male or female);

a = age (15 to 34);

e = years of education (0 to 18);

$i_{y,s,a,e}$ = per capita lifetime income in year y of persons of sex s, age a, and years of education e;

$yi_{y,s,a,e}$ = per capita yearly income in year y of persons of sex s, age a, and years of education e;

$sr_{y,s,a}$ = survival rate in year y of persons of sex s from age a-1 to age a;

ρ = discount rate;

g = real income growth rate;

[6] The equations and methodology for nonmarket human capital parallel that for market human capital.

$senr_{y,s,a,e}$ = school enrollment rate in year y of persons of sex s, age a, and years of education e, which is equal to zero from age 35.

For those aged 35 through 79, this equation simplifies to:

Equation (2) $i_{y,s,a,e} = ymi_{y,s,a,e} + (1+\rho)^{-1}(1+g)sr_{y,s,a+1}i_{y,s,a+1,e}]$

For persons aged 80 and older, per capita human capital is equal to:

Equation (3) $i_{y,s,80+,e} = [1 - (1+\rho)^{-1}(1+g)sr_{y,s,81+}]^{-1}yi_{y,s,80+,e}$.

which is the sum of an infinite series, and is equal to expected lifetime income given a yearly income $yi_{y,s,80+,e}$ that increases at an annual rate of g, a constant rate of survival $sr_{y,s,81+}$, and a discount rate ρ.

Total human capital is $i_{y,s,a,e}$ multiplied by the population with hours in each category, $pcount_{y,s,a,e}$. Nominal investment in births is the expected lifetime income of a newborn. Investment in education is the difference in lifetime income between an individual with the same characteristics and another, with one currently enrolled in school and the other not so. Depreciation from aging and deaths is deducted from gross investment. The human capital consumption component values time not spent in sleep, personal maintenance, education, or work at the market (opportunity cost) wage. There are some methodology timing differences in the 2016 Christian and 2019 Fraumeni and Christian paper, versus the 2017 and 2021 Fraumeni, Christian, and Samuels paper and the much earlier Jorgenson and Fraumeni papers.

Human capital quantities in the Jorgenson and Fraumeni co-authored papers were measured with Törnqvist indexes; in the papers co-authored by Christian or Fraumeni, Christian and Samuels or Fraumeni and Christian they are measured with Fisher indexes, with the exception of quantities such as net investment, which can include negative components. Aggregates that include human capital components are computed with Törnqvist indexes. Unless movements in the index components are large, Fisher and Törnqvist indexes result in very similar time series. Prices are implicitly determined from the nominal values and the quantities.[7] Fisher indexes are a geometric average of Paasche and Laspeyres indexes. As previously noted, with a Törnqvist index, the weights applied to the logarithmic rate of growth of the number of workers, are average shares of nominal lifetime income.

Previous Estimates of Productivity with J-F Human Capital for the United States

Previous estimates of TFP including J-F total (market plus nonmarket) human capital successfully dealt with the accounting identity (Fraumeni, Christian and Samuels 2015 and 2021, and Fraumeni and Christian 2017).[8] This was done by adding the value of nominal J-F lifetime human capital consumption and investment flows to labor input to create an augmented output.[9] Investment in education and births and time in household production and leisure – the latter the consumption component of human capital – are part of the index of augmented output, as are these components in the form of labor input part of augmented labor input. Because the accounting identity is maintained and the nominal value and the quantities of investment in human capital and time in household production and leisure are entered on the output and input side, it was implicitly assumed in the publications listed above that there is no TFP associated with human capital. TFP with and without human capital differ because the average nominal

[7] Quantities such as net investment, which can include negative components, are created using additive aggregation.
[8] In a November 22, 2018 presentation at a ESCoE human capital conference in London a market only TFP estimate was presented, but the methodology mimicked that in the published total TFP methodology with J-F human capital market and nonmarket inputs and outputs.
[9] However, as J-F human capital stock includes current labor income as does market labor input, the nominal dollar value of gross investment was too large.

share weights on the rate of growth on the other output and input components become much smaller when human capital is added to the production model. The growth rates of the human capital stock flow components are identical on the output and input side of the model. Table 1 shows that the impact of including human capital on average nominal shares in the most recent publication is very significant as is the effect on TFP.

Table 1: Impact of Including Human Capital Stock on Average Nominal Shares and Total Factor Productivity (TFP), 1949-2013					
	Average Nominal Shares[10]		**Average Nominal Shares**[11]	**TFP**	
Consumption with HC	.366	**Capital Input with HC**	.089	**With HC**	.18
Consumption without HC	.670	**Capital Input without HC**	.425		
Investment with HC	.634	**Labor Input with HC**	.911	**Without HC**	1.02
Investment without HC	.330	**Labor Input without HC**	.575		

Source: Fraumeni, Christian, and Samuels (2021) and the Christian data underlying that paper.

Revised Production Model with Fraumeni Market Lifetime Hours Human Capital for the United States

It is simple to maintain the nominal dollar accounting identity; the challenges are to remedy the stock and flow mismatches and to deal with the input inconsistencies and vintage effects.

One possible solution to remedy the stock and flow mismatches is to modify J-F lifetime income methodology by measuring market human capital with a stock of current and future market hours input. Both current and future hours are part of the stock. Accordingly, human capital enters into the production model through a Törnqvist index with the average shares of the current labor input in total input weighting the logarithmic growth rate of the hours stock. In any year, say

[10] Consumption with human capital includes consumption in Gross Private Domestic Product (GPDP) and time in household production and leisure; the latter is a nonmarket human capital component. Investment with human capital includes investment in GPDP and both market and nonmarket human capital investment. See Fraumeni, Christian, and Samuels (2021).

[11] Capital input includes GPDP capital input as defined in Fraumeni, Christian, and Samuels (2021). Labor input with human capital includes time in household production and leisure and both market and nonmarket human capital investment as labor input (Fraumeni, Christian, and Samuels, 2021).

2000, the quantity of the Fraumeni market lifetime hours stock is a summation of future hours expected to be worked by gender, age, and education based on hours worked of those older in 2000. Although individuals younger than 35 may complete an additional year of education in the future, the current level of education was maintained in the summation of expected future hours worked. Future education is an investment; substantial physical capital additions, renovations and reconstruction are also considered an investment. The use of hours for those older in a given year is similar to how nominal lifetime income is constructed as nominal total lifetime income for any year is the summation of nominal lifetime income of those older in that year, but with a rate of growth and a discount rate factored in as to adjust for nominal values. Such an adjustment is not needed for hours as hours are a homogeneous quantity. Once these new constructs are created, with an index of output and input, TFP can be determined, however vintage effects can impact on the accuracy of the TFP estimates because use of either physical or human capital hours stocks require a constant quality assumption, even with rates of growth weighted by current nominal physical or human capital average service flow shares.

The basis for current and future lifetime labor input are the hours, compensation and educational attainment Christian data underlying Christian (2016). With this data, Törnqvist indexes can be created with current earnings as the basis for the average nominal shares. The total number of categories (by gender, age, and education level) from the Current Population Survey (CPS) data base which have nonzero hours to allow for the creation of an hours stock is over 2,000 for each year.[12] As previously noted, both physical and human capital input from stock quantities rely on the assumption that the quality of the input by category is constant over time, an assumption that

[12] The March supplement to the Current Population Survey (CPS) is the source for the data on hours worked and earnings and the October CPS supplement is the primary source for the data on educational attainment.

is violated in the presence of any significant vintage effects.[13] Both physical and human capital stocks in all likelihood are mismeasured, the former because service lives, depreciation rates and efficiency-age shapes are rarely updated, thereby missing possible vintage effects; human capital stocks because of the lack of efficiency adjustment of hours and the possible presence of vintage effects. Hours efficiency adjustment is the focus of this section.

A first step in construction Fraumeni adjusted hours measures before estimating TFP is to remove the inconsistency between physical and human capital by efficiency adjusting hours worked as individuals age. The Programme for International Assessment of Adult Competencies (PIAAC - OECD, 2019) results support the notion that the efficiency of hours worked by individuals vary by age.[14] As a starting point, the efficiency of hours worked will be allowed to vary by age based on the PIAAC results. One difference from physical stocks which decline in efficiency as assets age, hours will be allowed to increase in efficiency as younger workers age, before hours efficiency will be allowed to decline in efficiency, at least through age group 55 and over.

There are other possible factors that could be used to determine worker efficiency. Paullin (2014) has listed a number of these as they impact on what she calls “mature” workers (see table 3, below, from Paulin).[15]Although she notes that mature workers are thought to be those generally

[13] Labor input, measured in any way (for example with hours of number of employees) also requires constant quality. A labor input measure with hours is preferred to a stock labor input measure (for example employees) as the number of future years entering into a calculation for a specific year increases the likelihood of a vintage effect occurring.

[14] See Figure 9 of OECD 2019 which shows literacy and numeracy scores of individuals by a representative sample of age groups who participated in PIAAC both in 2012-2104 and in 2017. This figure shows that differences occurred as individuals aged with results from participants in the 2012-4 and 2017 U.S. surveys. The target population for PIAAC is the non-institutionalized population, aged 16 to 65 years, residing in the country at the time of data collection, irrespective of nationality, citizenship or language status.

[15] Reprinted from Paullin, 2014, © Society for Human Resource Management.

above age 50 or 55, she also notes that age is not the only indicator of maturity.[16] There are no numerical indicators of the impact on younger and mature workers in her analysis, accordingly, in this paper examining experimental efficiency adjustments, the PIAAC skill indicators form the basis for efficiency adjustments. A further literature survey may well reveal other possible measures.

Table 3: Relationship Between Job Performance and Age

Aspect of Job Performance	Relationship with Age
Core task performance	No consistent relationship up to mid-60s
Performance quantity	May be higher for younger workers
Performance quality	May be higher for mature workers
Organizational citizenship behaviors	Higher for mature workers
Counterproductive work behaviors	Lower for mature workers
Self-reported health problems	Similar levels through middle age, then higher levels with advancing age
Clinical indicators of health	Worse for mature workers
Resistance to change	May be lower for mature workers
Innovative behaviors	No relationship
Organizational commitment	Higher for mature workers
Turnover intentions	Lower for mature workers

Table 2 shows the PIAAC results and the adjustments to hours based on the 2012 PIAAC.[17] This will not eliminate the possibility of vintage effects to which Inklaar and Papakonstantinou (2020)

[16] The report states on p. 2 "No matter which number is chosen, chronological age is not the best way to define the mature worker. People vary in terms of when and how they experience aging and whether they perceive themselves as aging. Factors that should be taken into account in addition to chronological age include physical, mental and emotional health; career stage; job tenure; and life experiences."
[17] Although Figure 9 included a breakout of the 55 and over age group into 55-59 and 60-64 age groups, this breakout is not used in this paper's analysis under the assumption that PIAAC statisticians were less comfortable with a more detailed age breakout than with the 55 and over age breakout as the US report did not show the more detailed age breakouts.

and Bowlus and Robinson (2012) refer, but it will recognize that efficiencies differ by age.[18] [19] PIAAC U.S. literacy and numeracy age efficiency profiles for those who took part in both the 2012/2014 and 2017 PIAAC do not reveal vintage effects, but they may occur over different time periods.[20] Note that as shown in Table 2 the problem solving skill is the only one that monotonically declines by age group. In addition, across all skills, the largest percentage decrease is between those aged 35-44 and 45-54.

Table 2: Hours Efficiency Age-Adjustment Based on 2012 PIAAC

	Age Groups				
Skill	**16-24***	**25-34**	**35-44**	**45-54**	**55 & over**
Literacy	272	275	273	266	263
Numeracy	249	260	258	250	247
Problem Solving in Technology Rich Environments	285	283	279	271	267
Average Score	269	273	270	262	259
Hours Efficiency Adjustment**	.985	1.000	.990	.960	.950

*The hours efficiency adjustment listed in this column is applied to those aged 15-24.
**No significant differences in averages:

Literacy: 24 or less & 25-34, 24 or less & 35-44, 45-54 & 55 & over
Numeracy: 24 or less & 45-54, 24 or less & 55 & over, 25-34 & 35-44, 45-54 & 55 & over
Problem Solving: 24 & less & 25-34, 25-34 & 35-44, 45-54 & 55 & over

[18] Inklaar and Papakonstantinou (2020, p. 24) write in their conclusions section that a standard assumption used in growth accounting: "an hour worked by a worker of a given type,...., represents a constant amount of labor services per hour worked over time. Yet if there are vintage effects, this assumption may be violated."
[19] Inklaar and Papakonstantinou (2020) conclude that the vintage effects are important in the U.S. between 1975 and 2014, a time period which is almost identical to that to be covered in the proposed paper. Hudomiet and Willis (2021) analyze how computerization affected the labor market outcomes of older workers between 1984 and 2017. Bowlus and Robinson (2012, p. 3514) conclude that "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 used to estimate MFP only deal with composition, they cannot capture a large part of the quality change."
[20] See Figure 9 of OECD 2019. This report stated that the problem solving in technology rich environments average score marginally improved between 2012/2014 and 2017. Full results for the 2017/2018 PIAAC are not yet available when the analysis underlying this paper was completed.

Because efficiency is set to 1.0 in the age group (25-34) with the highest average skill score, adjusted hours are lower than unadjusted hours for all other age groups. Figure 1 shows the average percentage decrease between unadjusted and adjusted hours. The percentage reduction drops from 2.06 percent in 1975, to the smallest reduction of 1.75 percent in 1987, before increasing to 2.41 percent in 2013. This reduction is driven by the size of the working population, the hours the younger, prime age, and older work, and the increasing labor force participation of women. Most noticeably, the workforce has aged as the post-World War II baby-boomers aged. The boomer birth rate peaked in 1947, but individuals born between mid-1946 and mid-1964 are considered baby-boomers.[21] [22]

The following three figures are unadjusted hours pyramids with information on the percentage of total hours worked by gender. The percentages for males are shown as negative numbers to facilitate construction of the pyramids; in fact they are all positive and equal to the absolute value of the negative figure shown. The sum of all percentages in a pyramid for a year is 100 percent. The pyramids demonstrate the changes in hours worked in 1975 and 2013 and in 1987, the year of the smallest efficiency reduction by age.

[21] National Office of Vital Statistics (1950), Table Y, p. XIX.
[22] Colby and Ortman (2014), p. 2.

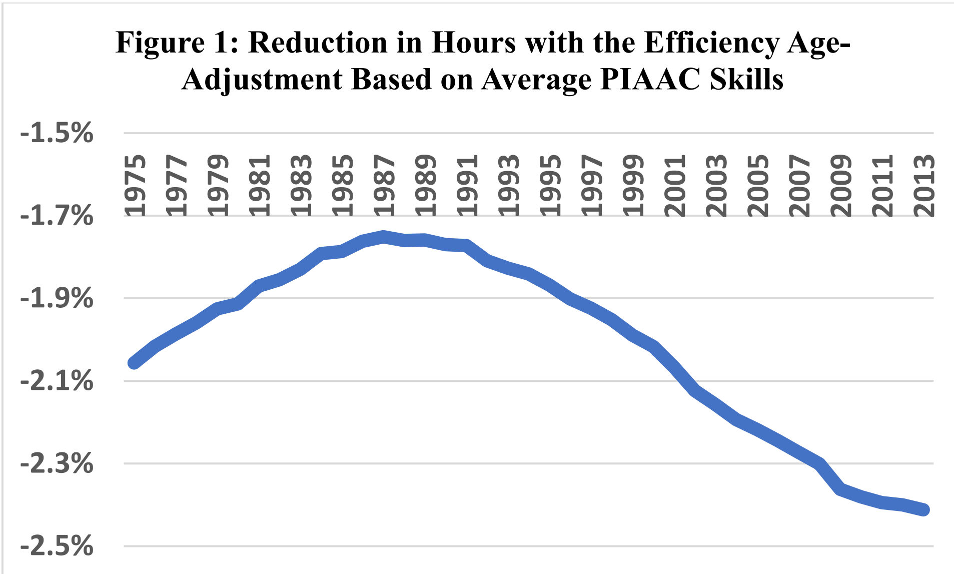


Figure 1: Reduction in Hours with the Efficiency Age-Adjustment Based on Average PIAAC Skills
-1.5%
-1.7%
-1.9%
-2.1%
-2.3%
-2.5%
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007
2009
2011
2013

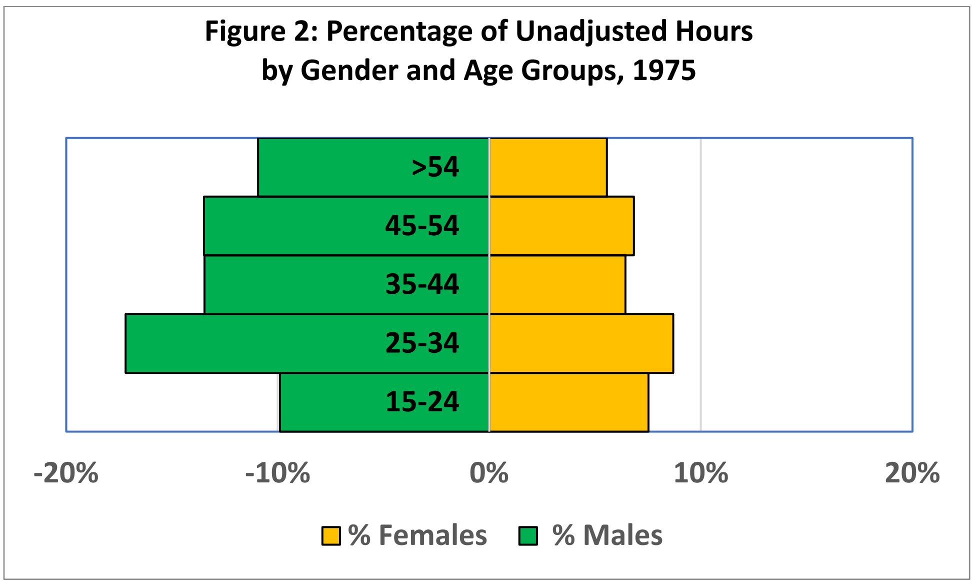
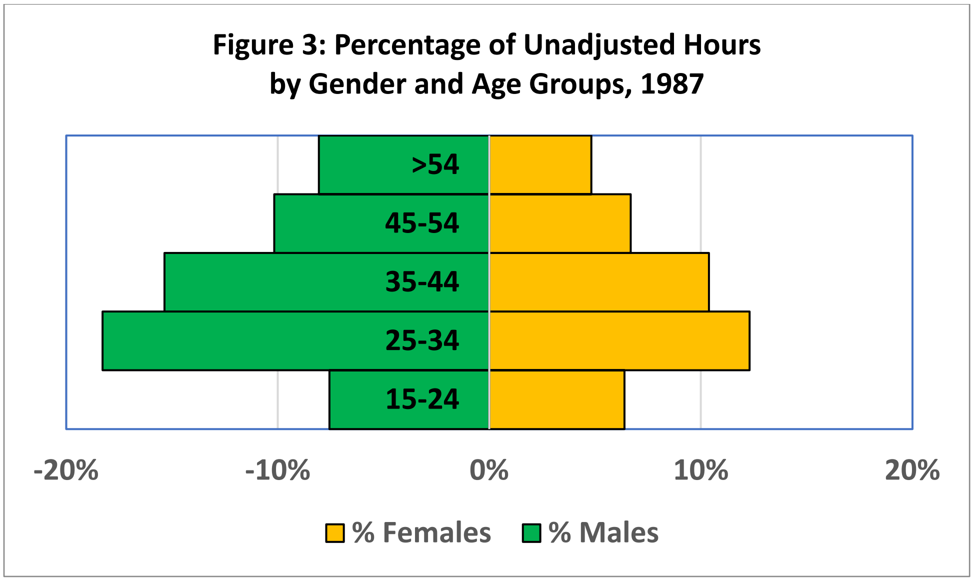
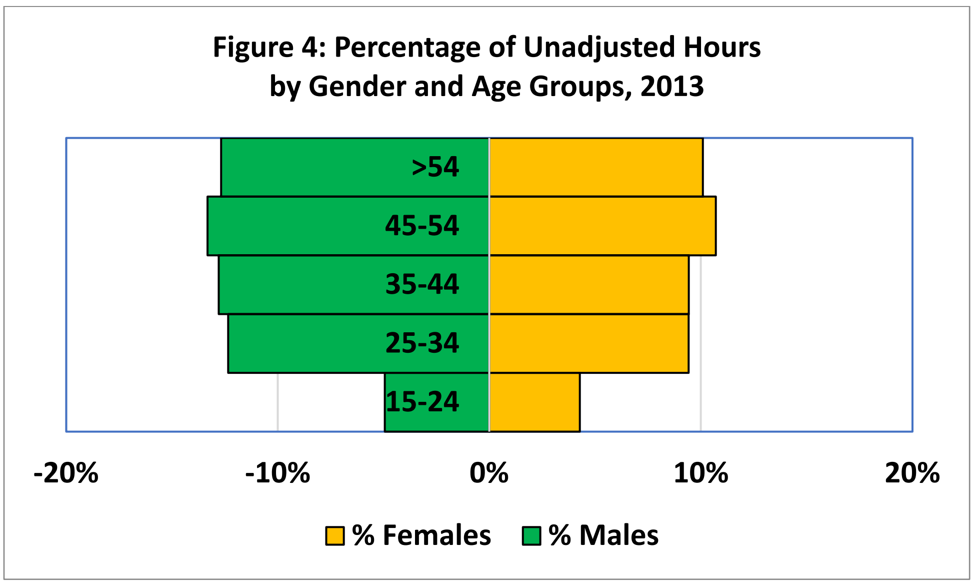


Figure 2: Percentage of Unadjusted Hours by Gender and Age Groups, 1975
>54
45-54
35-44
25-34
15-24
-20%
-10%
0%
10%
20%
% Females
% Males





The shapes of these unadjusted hours pyramids show the changes over time. 1987 is the year in which the percent of hours worked by individuals with the highest average PIAAC skill rating, those aged 25-34, is at its maximum of the whole period, 1975-2013. With a pyramid shape on the youngest age group base (Figure 3), it is not surprising that the percentage difference between unadjusted and adjusted hours is the smallest. Although the 25-34 block is the largest of all blocks in 1975 (Figure 2), the differences in the block widths is much less than in the 1987 pyramid. In 2013 (Figure 4), the block widths for all age groups except for that of those 15-24 is most similar, reflecting in part the aging of the baby-boomers. In addition, between 1975 and 2013, the percentage point difference between hours worked by males and that by females for all age groups dropped by at least half, reflecting the higher labor female force participation rates by 2013. For these reasons, the percentage difference between unadjusted and adjusted hours is at its maximum in 2013.

There are two alternative efficiency adjustments from PIAAC for which data is available from the Christian (2016) data set used in this paper: One by gender (table 3) and the other by qualifications (table 4).[23] Efficiency age-adjusted hours are the basis for the analysis in this paper because physical capital stocks are efficiency age-adjusted. Note that the Törnqvist indexes of the quantity of labor input using current adjusted hours are identical regardless of which of the three alternatives are employed.[24] However, figures 5 and 6 show that the efficiency adjustments by gender and qualifications vary significantly from that by age (figure 1). Figure 5 shows the smallest reduction in hours worked. The adjustment factor for females is .975, which means that the reduction could be at most 2.5 percent if all workers were females. The reduction increases monotonically until the early 90's, after which female hours as a percent of male hours no longer increases monotonically (see the right-most vertical axis). Figure 6 shows by far the largest reduction in hours worked as the qualifications of individuals varied significantly between 1975 and 2013.[25] In both 1975 and 2013, the largest percentage of hours worked is by individuals with ISCED 3 (2 years+) qualifications, but the percentage has decreased substantially for both males and females by 2013 (see figures 7 and 8). Conversely, the percentage of hours worked with

[23] A description of ISCED categories is in the appendix.
[24] Because these efficiency adjustments do not vary by year and the Christian (2016) data is available for all of the possible categories, the log growth rates by category do not change.
[25] In the Christian (2006) data, average hours worked by all individuals by gender, age and educational attainment are reported. Since not all individuals engage in market work, the reported qualifications are not for workers only, rather for all individuals in a gender, age and educational attainment category.

ISCED 1 or 2 qualifications are the smallest of all qualification categories by 2013. At the same time by 2013, the percentage of hours worked at an ISCED level 5 for both males and females have all increased and are very similar. Optimally, average skills by age would be available by gender and qualifications, but this is unlikely given the size of the PIAAC sample.

Table 3: Hours Efficiency Gender-Adjustment Based on 2012 PIAAC		
	Gender	
Skill	**Male**	**Female**
Literacy*	270	269
Numeracy	260	246
Problem Solving in Technology Rich Environments	280	275
Average Score	270	263
Hours Efficiency Gender-Adjustment	1.000	.975

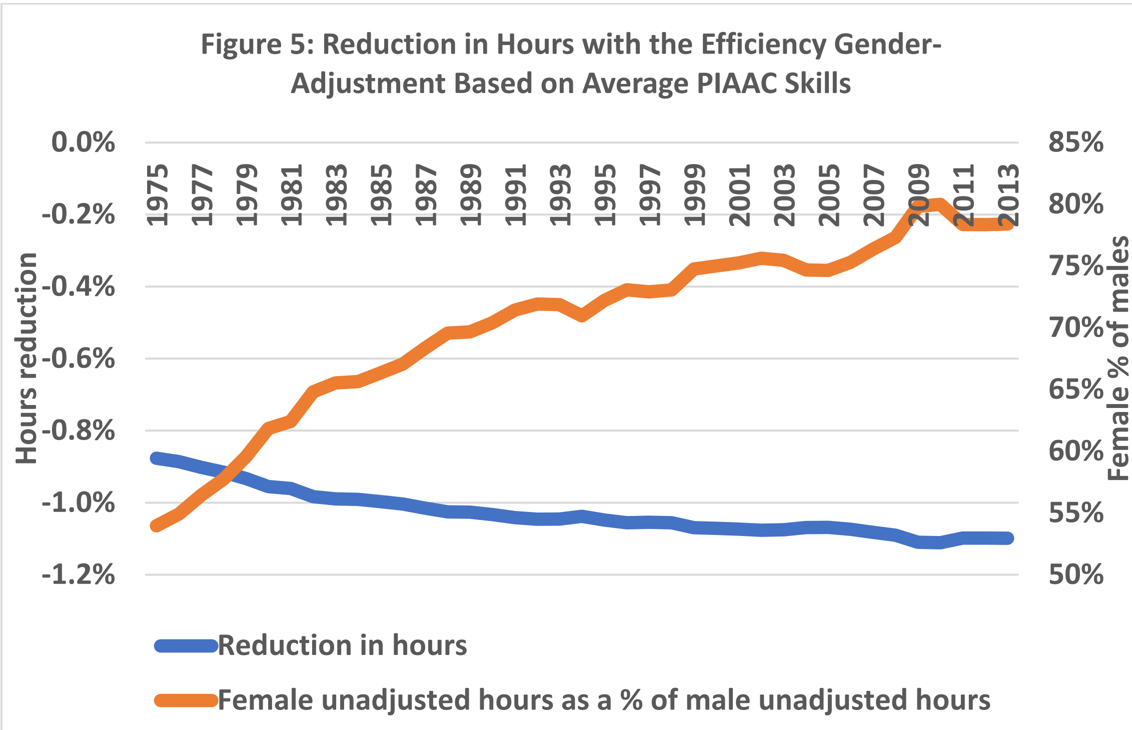
*There is no significant difference in literacy skill averages between males and females.

Table 4: Hours Efficiency Qualification-Adjustment Based on 2012 PIAAC								
	ISCED Number* **							
Skill	**1**	**2**	**3 (2 yr +)**	**4 A-B**	**5 B**	**5 A (BA)**	**5 A (MA)**	**6**
Literacy	190	237	261	266	283	298	310	310
Numeracy	164	210	242	250	267	287	302	302
Problem Solving in Technology Rich Environments	206*	261	267	269	282	296	301	301**
Average Score	187	236	257	262	277	294	304	304**
Hours Efficiency Qualifications-Adjustment*** **	.613	.775	.843	.860	.911	.965	1.000	1.000

* Problem solving score assumed to be 79 percent of ISCED 2 score as this is the average that the ISCED 1 score is of the ISCED 2 score for the two other skill categories.
** ISCED 6 score is assumed equal to the ISCED 5 A score.
*** The ISCED 1 score is used for those with less than 9 years of school completed. The ISCED 2 score is used for those with 9-11 years of education completed, the ISCED 3 (2 yr +) score is used for those with 12 years of education completed, the ISCED 4 B score is used for those with 13 years of education completed, the ISCED 5 B score is used for those with 14 or 15 years of education completed, the ISCED 5 A (BA) score is used for those with 16 years of education completed, and the ISCED 5 A (MA) score (used for ISCED 6 problem solving) is used for those with 17 or 18 years of education completed.
**** No significant differences in averages:

Literacy: ISCED 3 & ISCED 4 A-B, ISCED 5A (BA) & ISCED 6,
ISCED 5A (MA) & ISCED 6
Numeracy: ISCED 5A (BA) & ISCED 6, ISCED 5A (MA) & ISCED 6

Problem Solving: ISCED 3 A-B-C & ISCED 4 A-B,
ISCED 5A (BA) & ISCED 5A (MA)



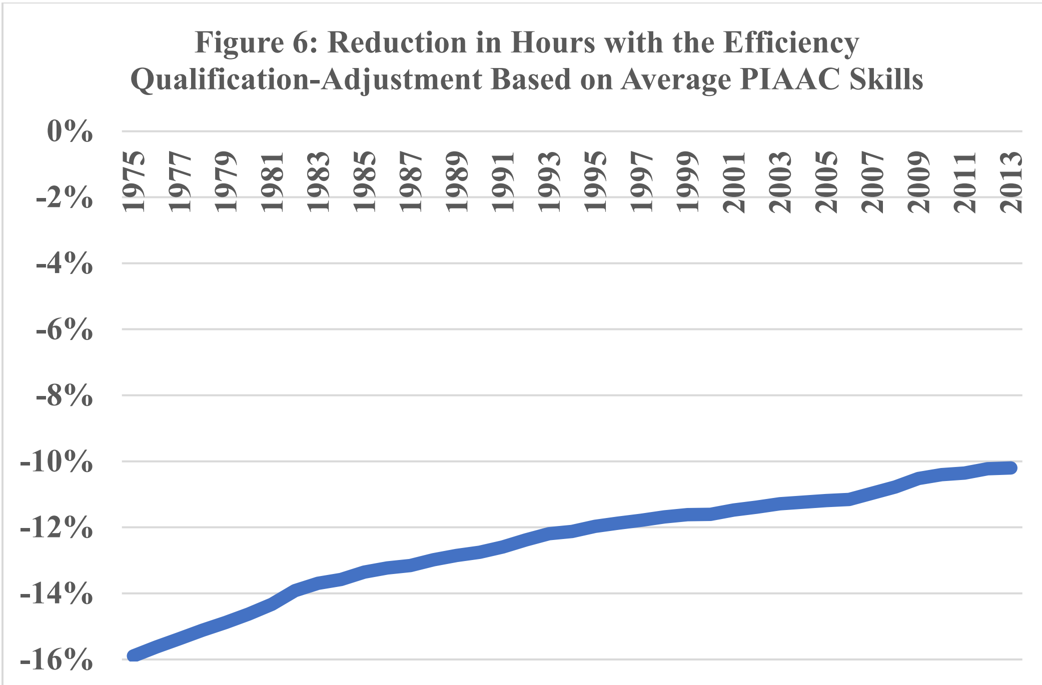


Figure 6: Reduction in Hours with the Efficiency Qualification-Adjustment Based on Average PIAAC Skills
0%
-2%
-4%
-6%
-8%
-10%
-12%
-14%
-16%
1975
1977
1979
1981
1983
1985
1987
1989
1991
1993
1995
1997
1999
2001
2003
2005
2007
2009
2011
2013

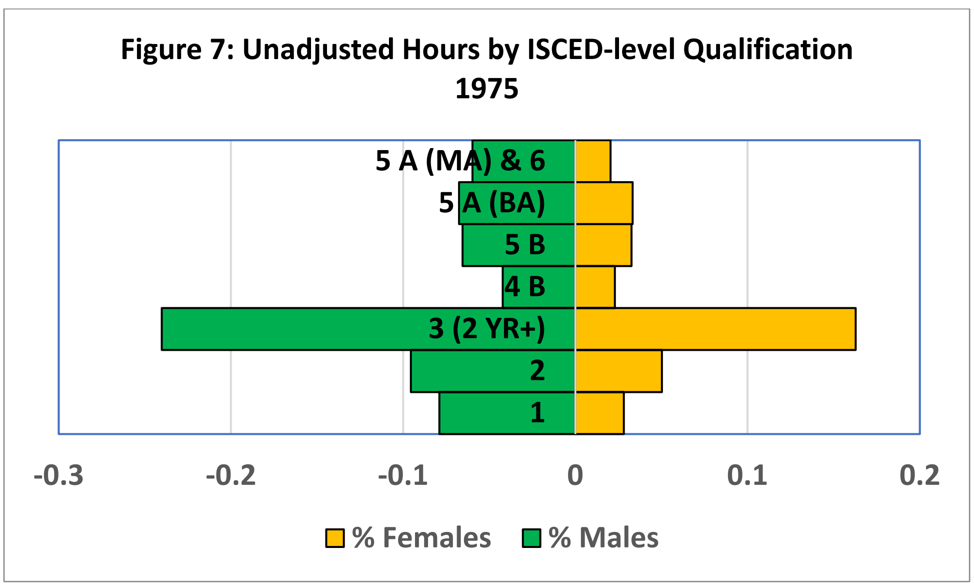
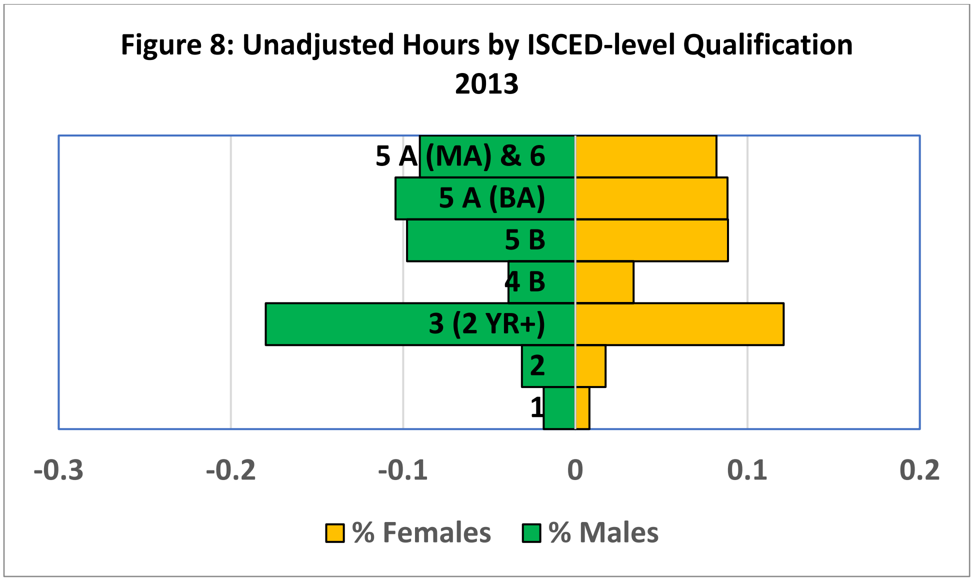
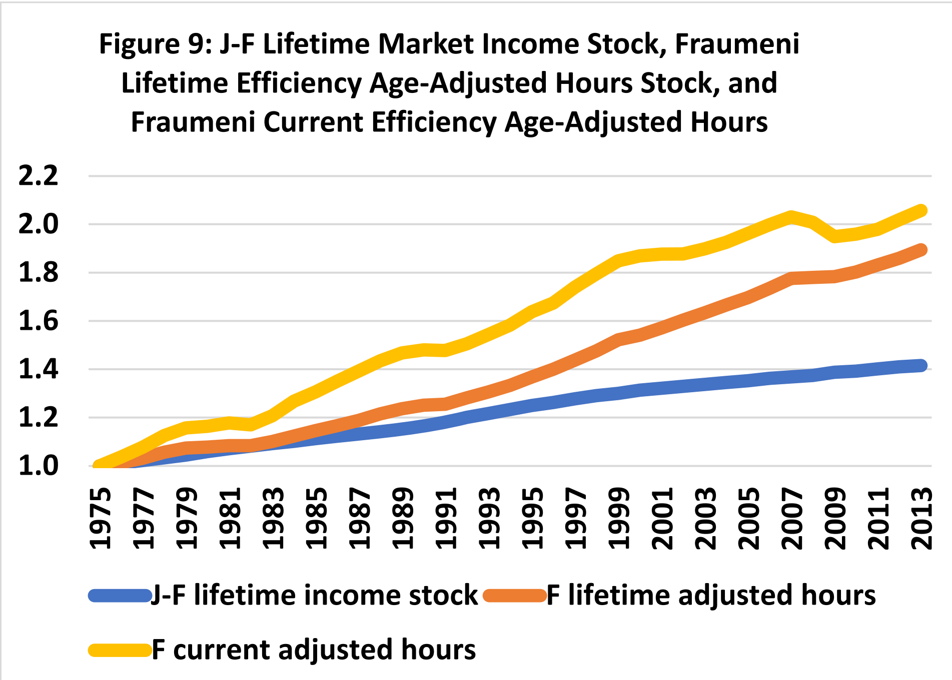


Figure 7: Unadjusted Hours by ISCED-level Qualification 1975
5 A (MA) & 6
5 A (BA)
5 B
4 B
3 (2 YR+)
2
1
-0.3
-0.2
-0.1
0
0.1
0.2
% Females
% Males



The next figure, figure 9, shows J-F market lifetime income and Fraumeni (F) efficiency age-adjusted lifetime hours stocks, as well as F efficiency age-adjusted current hours, all normalized to 1.0 in 1975. Since J-F depends upon logarithmic rates of growth of population and F depends upon logarithmic rates of growth of hours, it is no surprise that the F stock is always above the J-F stock. From 1975-2013, annual male hours grew at about one percent per year and annual female hours grew at about two percent per year, while the population grew at about one percent per year. The figure is normalized to one in 1975 as F lifetime and current hours indexes are both normalized to nominal labor input (earnings) in 2012, but J-F human capital stock is normalized to nominal lifetime income (earnings) in 2012. Without the normalization to one in 1975, the J-F lifetime income index line would be far above either F versions. A sense of the magnitude of the difference is shown in table 2 in the comparisons of average nominal shares in a production model without human capital and one with J-F human capital. F lifetime adjusted hours typically grows at a slower rate than F current hours as the lifetime hours base is so much larger than current hours. J-F lifetime income measures continue to be valuable as they can be directly incorporated into NIPA and SNA-like accounts as they allow estimation of investment, stock revaluation, depreciation, and so forth.



Vintage Effects Literature and Estimation Results in a Market Production Model:

The Bowlus and Robinson (2012) and Inklaar and Papakonstantinou (2020) results for the U.S. are central to one approach to possibly partially remedy the vintage effects problem. Inklaar and Papakonstantinou (IP hereafter), followed the methodology of Bowlus and Robinson (BR hereafter), but applied the methodology to compare vintage effects of the U.S. versus six European countries. By looking at a flat spot in high-skilled worker Consumer (CPI) deflated wage profiles, BR attempted to isolate vintage effects. Three categories of male employees were identified for the U.S. by IP: High-skilled workers (those having completed tertiary education), medium-skilled workers (those having completed secondary education) and low-skilled workers (those not having completed secondary education). It was assumed that the flat spot identified in the high-skilled worker wage profiles occurred three years of age earlier for medium-skilled workers and six years earlier for low-skilled workers. IP adopted the BR flat spot range for U.S. high-skilled workers. They took the log of median wages paid by category deflated by the consumer price index for full-time full-year (FYFT) males to identify the vintage effects over time. (See Figure 1 below, on p. 3 in their paper, produced with a LOWESS smoother with a .8 bandwidth parameter and figure 1 notes from their paper as an example). IP's estimates for FYFT male workers that were not self-employed indicated that labor services per hour (quality) increased by 25 percent between 1975 and 2015, with most of the increase (19 percent) occurring between 1995 and 2005. For the same FYFT male category of workers, but having medium skills, labor services per hour decreased 10 percent, with most of the decrease occurring between 1975 and 1995 and trending inconsistently subsequently. For the same FYFT male category of workers, but having low skills, labor services per hour decreased substantially doing the same time period as those with medium skills, with a total decline of 20 percent for the whole period (IP, pp. 11-12). By age groups for U.S. high-skilled workers over the period 1995-2005, wages of young workers aged 26-35 increased by 6.2 percent, wages of middle-aged workers aged 36-49 increased by 12.6 percent, and wages of old workers aged 50-59 decreased by 1.2 percent (table 9 of IP).

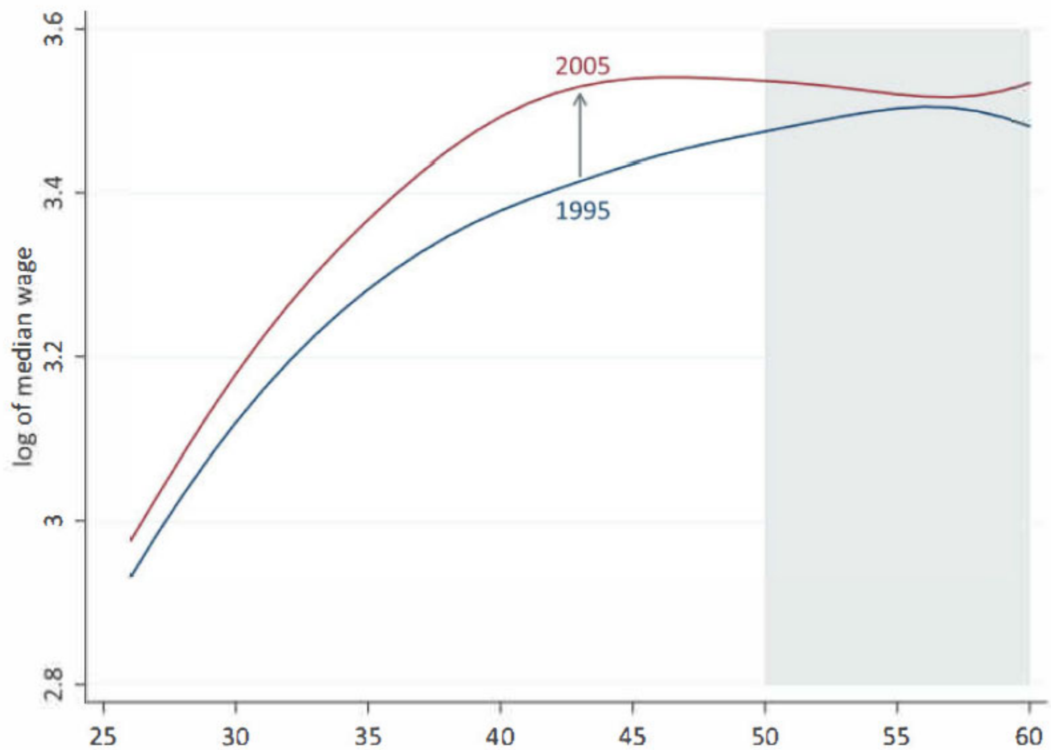


Figure 1. Age-Wage Profile for High-Skilled Workers in the United States, 1995 and 2005.

Source: Calculations based on the Current Population Survey from IPUMS-CPS (Flood et al., 2015).

Notes: The figure shows the results for a LOWESS smoother with bandwidth parameter 0.8 over the median wage at each age for full-time, full-year male employees with a bachelor's degree or above. Wages are deflated using the consumer price index. [Colour figure can be viewed at wileyonlinelibrary.com]

IP realize that such vintage effects can occur for several reasons: The quality of students, the quality of higher education and changes in workers' human capital production function. It is possible that when more students attend higher education, the average quality of graduates given a constant quality of higher education may decline. IP also note that it is also true that the quality of higher education, through more work relevant and better courses, or the human capital production function, through experience and on-the-job-training, may both improve, so that the net effect is uncertain.

Both BR and IP primarily used median wages for full-time full-year (FTFY) males. IP note the difficulty of including females because of the changing labor force participation of females during the 1975-2014 time period. IP did conduct sensitivity tests by including all males that worked at least five hours per week for at least five weeks in a year, removing the top and bottom five per cent of wages in the flat spot area, and focusing only on certain industries. The pattern for high-skilled workers is the same as for the baseline FTFY case, however, there is not a clear pattern for the medium-skilled and low-skilled workers. IP concluded that there was "again, no substantial deviation from the baseline results" (IP, p. 17). The sensitivity tests are relevant as the estimates provided later in this paper include all workers with hours, with data from the March CPS supplement and from the October CPS supplement, while both BR and IP's sample is from the March CPS supplement only.

A figure as similar as possible, given the differences in the data sample, to the one above is constructed with a LOWESS smoother with a .8 bandwidth parameter using the Christian (2016) data (figure 10).[26] Since the Christian data set includes all hours worked by high-skilled males and median wages cannot be constructed from that data set, only average wages, it is difficult to know why the shape differs from that in IP. Comparing figure 10 to figure 1 from IP, note that the 2005 profile is not substantially higher in the middle of the age distribution than in earlier years. There is a flat spot, but it appears to begin before age 50, which is earlier age than in IP.[27]

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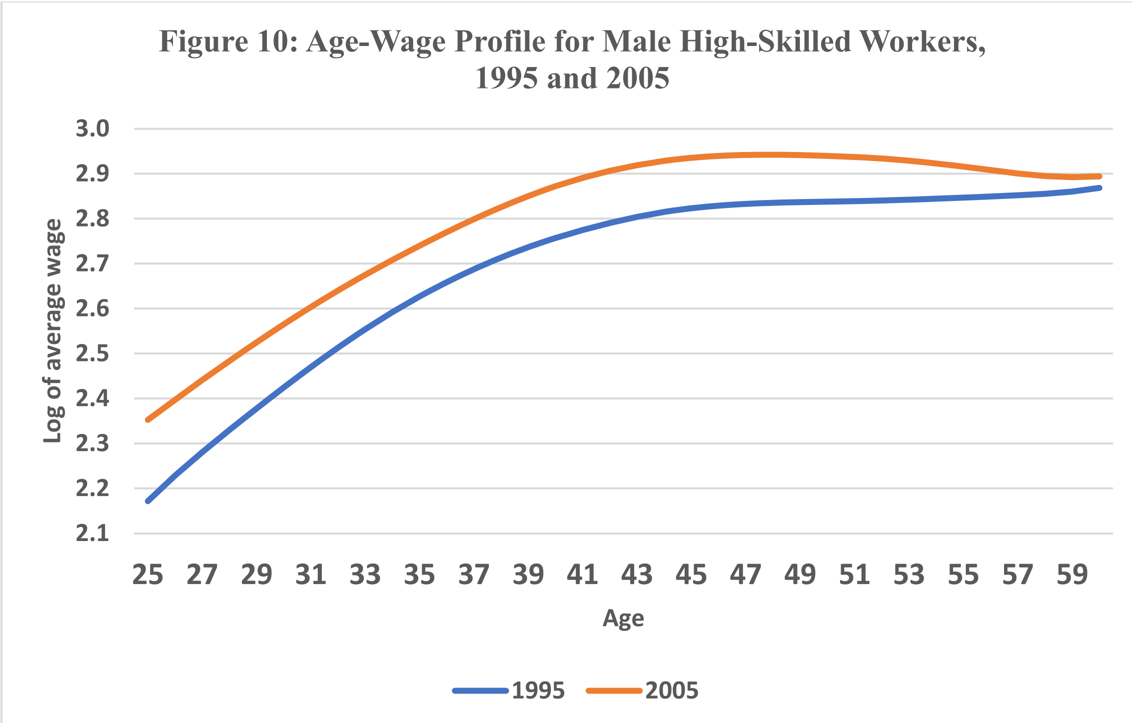
[26] The same U.S. Bureau of Labor Statistics CPI used in the IP paper: CPI-U, All urban consumers, all city average, not seasonally adjusted, is used in figures 10 and 11.

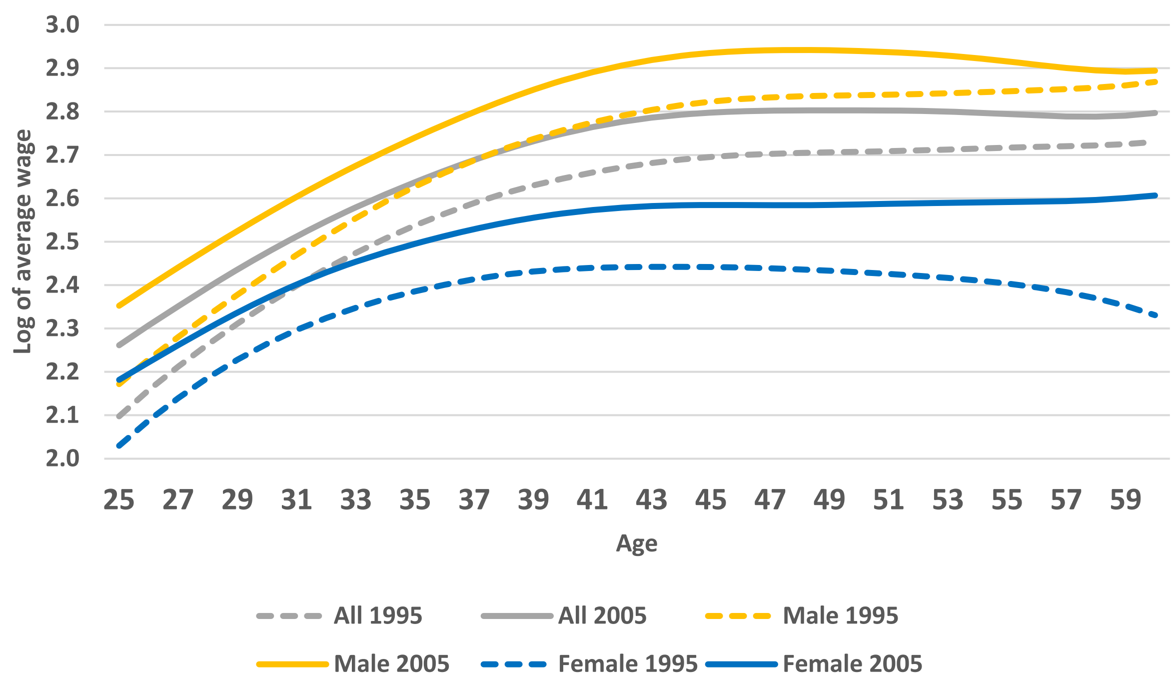
[27] Inklaar has been contacted to obtain a Consumer Price Index (CPI) wage deflator identical to used in IP and to determine how the 19 percent was calculated. In both figures, a LOWESS smoother is used with a bandwidth of .8. At least part of the difference in the y-axis scale is probably due to how the CPI deflator is indexed, e.g., set to 100 or 1.0 in which year.



Hudomiet and Willis (2021) looked at the impact of computerization, which largely took place in the 80's and 90's, on the labor market situation of older workers. They documented that older workers started using computers later than younger workers until about the early 2010's. They "found that the knowledge gap shortened the working life of older workers, it pushed many full-time workers into part-time jobs, and it lowered their wages." (p. 34) Females, middle-skilled workers, and older workers experienced larger effects than others. Their research documented the existence of computer-related vintage effects. IP note that age-related technological factors may impact particularly younger high-skilled workers (p. 4); the PIAAC problem solving in technology rich environments skill scores by age support this notion.

Similar LOWESS smoothed curves are constructed for all high-skilled workers and for female high-skilled workers for 1995 and 2005. Figure 11 shows these curves for high-skilled males as well. All show a vintage effect and all, except for the 1995 curve for females, show a flat spot range. The average annual percentage difference between the 1995 and 2005 deflated wages unsmoothed is 3.1 percent for all workers, 3.3 percent for males, and 4.7 percent for females, compared to 1.9 percent in figure 1 for FTFY males.[28]

Figure 11: Age-Wage Profiles for High-Skilled Workers
1995 and 2005



Experimental Vintage Adjustment for a Market Production Model Based on IP and BR

In this paper a different approach is used to identify vintage effects. As the problem with the Jorgenson model is the assumption that the quality of inputs is constant over time, changes in the quality of the hours labor input is the gauge used to determine the extent of vintage effects. A shortcoming with the IP vintage measure is the difficulty of determining a real wage. A CPI

[28] It is unknown if the 19 percent vintage effect over all ten years in the IP paper is based on the unsmoothed or smoothed data.

deflator measures a real wage by the cost of the goods and services that can be bought with the wage money income, not the marginal product of a worker.

Even with a constant quality vintage framework, there are decisions to be made in constructing the experimental efficiency adjustments, given age-adjusted efficiency hours: Whether to use labor input based on efficiency age-adjusted current hours or labor input based on efficiency age-adjusted lifetime hours. To avoid a more likely violation of the constant quality assumption with a stock than with efficiency age-adjusted hours, labor input based on efficiency age-adjusted current hours is the basis for possible vintage efficiency modifications. It is assumed that an assumption violation is more likely with a stock as a stock has current and future components, with current hours only having a current component. To aid in the worker scope decision, labor input quality (constructed with a Törnqvist index - per hour) by gender and the three skill categories for all individuals with hours worked with the efficiency age-adjusted hours is estimated. These categories are the same skill categories used in IP for FTFY males. As previously noted, the Christian data set does not allow applying the vintage effects only to hours of FTFY males with an efficiency adjustment, as it only includes information on average hours worked by age and education category, without further detail.

Figure 12 shows that it makes a difference if efficiency age-adjusted current hours rather than lifetime efficiency age-adjusted hours are the basis for estimation of TFP. These current and lifetime hours calculations are done across all categories when there are positive hours in the base year (2,000 in each year). Categories are by gender, single years of age, and single years of education. Except in 1976 and 1977, the differences in the TFPs are very small until 1985. In subsequent years, the fluctuations in TFP are similar.

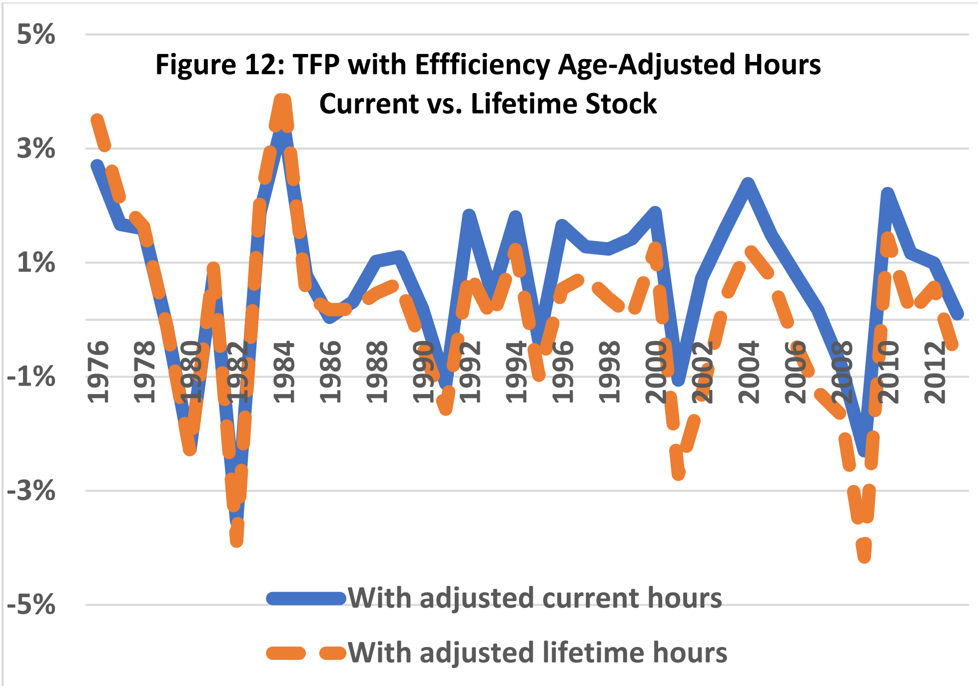
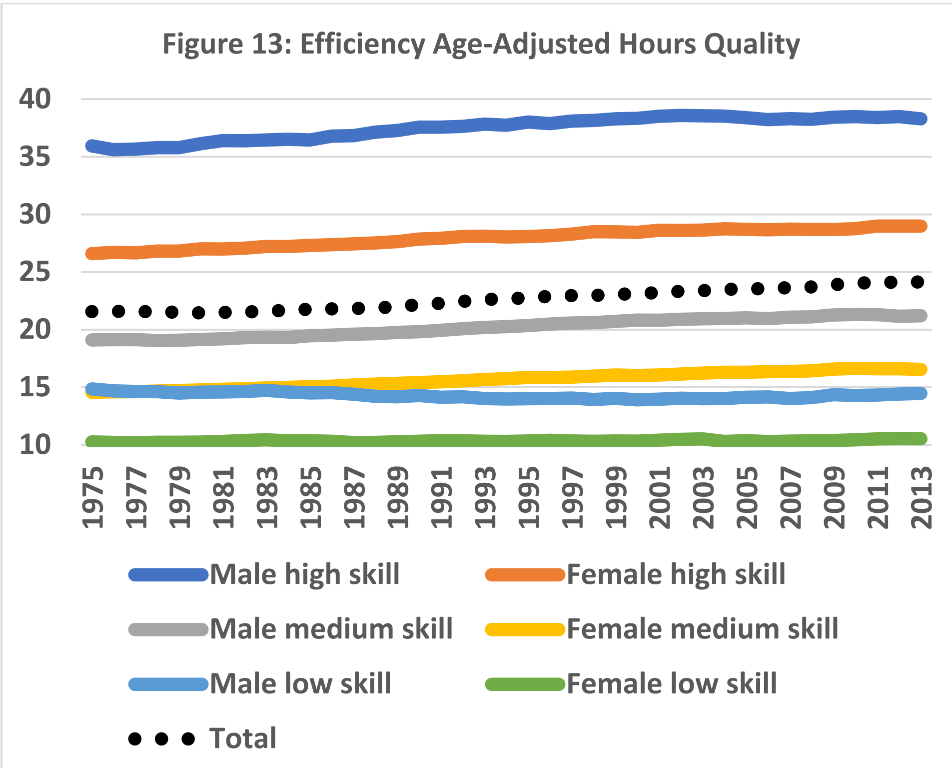


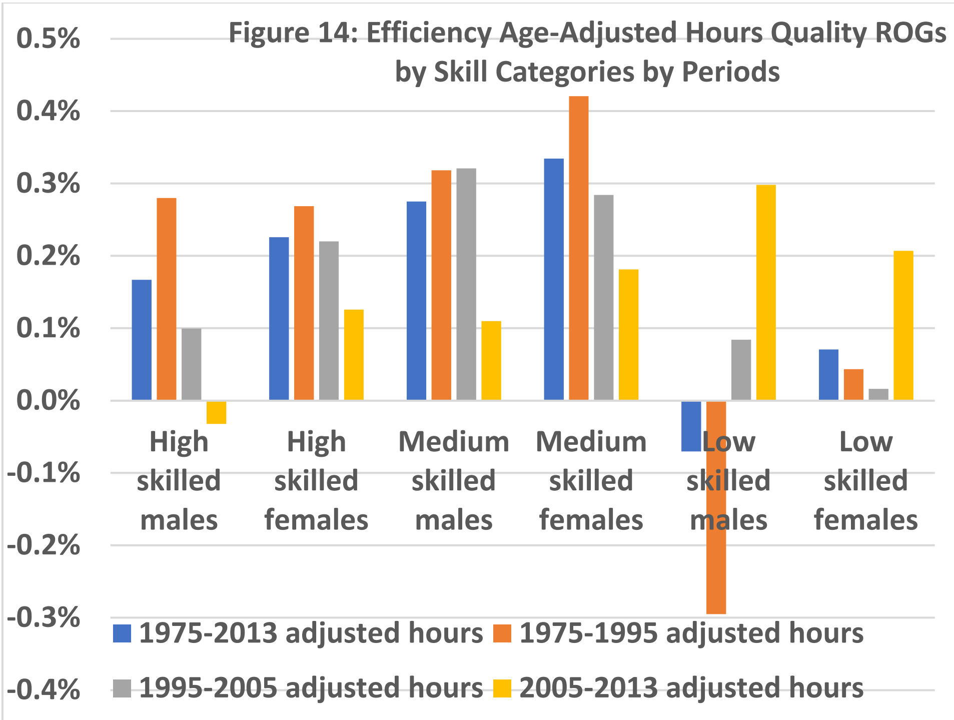
Figure 13 shows the efficiency age-adjusted current hours Christian data quality results. Quality or labor input per hour definitely varies by year by category, but as Figure 14 clearly shows and Figure 13 suggests, the average annual quality rates of growth for the whole period: 1975-2013 and the three subperiods: 1975-1995, 1995-2005, and 2005-2013, are quite low. Those by gender and skill categories vary from a high in 1975-1995 of .42 percent for medium skilled females to a low in the same subperiod of -.30 percent for low skilled males. The vintage results from IP particularly for FTFY high-skilled males (approximately 1.9 percent on average per year for 1995-2005) differed significantly from these results. Accordingly, the decision was made to not vintage adjust the efficiency age-adjusted hours using the IP results. The average quality rates of growth for the overall quality index, computed from the gender and skill Törnqvists, are .30 percent for 1975-2013, .27 percent for 1975-1995, .35 for 1995-2005, and .28 for 2005-2013. These vintage effects are much lower that those computed using the IP methodology. This analysis does not indicate which results are correct or that there are no vintage effects for the gender and skill categories, because of different IP's and this paper's worker coverage and possible issues with the Christian data base (e.g., different coverage in the March and October CPS supplements), therefore no conclusive conclusions can be reached.[29] More research is needed.[30] [31]



[29] A paper recently presented at an IARIW conference with reference to Frazis and Stewart (2004) noted that the more-educated workers in the Consumer Population Survey compared to the American Time Use Survey over-estimated hours worked and less-educated workers under-estimated hours worked (Eldridge, Pabilonia, and Stewart, 2021, p. 9).

[30] The quality results by gender and skill level with unadjusted hours vary slightly from those with adjusted hours; the absolute value growth rate greatest difference being .04 percent. For all subperiods, except for most of those for low-skilled workers, the quality growth rate with adjusted hours is greater than the quality growth rate with unadjusted hours growth.

[31] Labor productivity for 1975-2013 with adjusted vs. unadjusted hours by gender and skill level would be only slightly different as the output numerator would be identical and the rate of growth of adjusted vs. unadjusted hours rate of differs in absolute value by at most .02. The rate of growth of adjusted hours is lower than that for unadjusted hours except in the case of low skilled males and females (.01 percent higher for low-skilled workers).



To test what happens when hours are adjusted because of vintage effects, the high-skilled males efficiency age-adjusted hours are adjusted for vintage effects. The difficulty in making a vintage adjustment to hours is that hours appear in two places in the quality calculation: In the denominator and in the share weighted logarithmic rates of growth that form the labor input index. In the test, it was determined what the denominator hours would have to be in each year to maintain a constant quality for high-skilled males. The efficiency age-adjusted hours in each detailed category are then multiplied by the ratio of the constant quality denominator hours to the efficiency age-adjusted denominator hours. There are more than 175 of these categories per year with nonzero hours. The Törnqvist labor input index was then recalculated with the revised hours. As Table 5 indicates, the average quality growth rates for the vintage version versus the age only adjustment version are very similar for the period as a whole and for all subperiods except for 2005-2013. After the vintage adjustment, all but two of the last period's qualities to two digits to the right of the decimal are identical to quality in 1975.

Table 5: Comparison of Quality Growth Rates for High-skilled Males		
	Vintage & Age	**Age Only**
1975-2013	.18	.17
1975-1995	.29	.28
1995-2005	.09	.10
2005-2013	.00	-.03

Conclusion

Current hours worked and/or the lifetime stock of hours should be age and vintage efficiency adjusted and an index of those adjusted hours with current hours only, adjusted or not, should be the basis for a production model with TFP. PIAAC enables age adjustments, although clearly it would be preferred to have PIAAC-like information for years before 2012. Quality-based vintage adjustments are much more difficult to implement for two reasons. First, how to estimate constant quality as the basis for an efficiency adjustment given that hours appear in two places in quality derived from Törnqvist indexes? Second, although the March CPS Annual Social and Economic Supplement (ASER) is a representative survey, that certainly does not mean that all categories (over 2000 per year in the Christian sample with positive hours) are representative of all individuals in the category. Quality variations over time could be the result of differences in the statistical properties of the sample, rather than indicative of changes in quality. Certainly, the concern with the properties of the ASER sample led both BR and IP to base their featured results on FTFY males. Quality estimation over categories which are representative of their populations is preferred, however, aggregate quality changes over time could be the result of compositional changes rather than changes in the efficiency of hours worked of the underlying representative categories. Categories as detailed as possible are preferred as the assumption that productivity of all individuals in the category is the same is more reasonable. It is likely that both preferences (representativeness and detailed categories) cannot both hold at the same time. Lastly, it hopefully can be determined why the BR and IP approach results in a much larger estimate of vintage effects than one based on input quality. The bottom line is that much more research is needed, particularly by individuals knowledgeable about the statistical properties of the ASER (March CPS supplement) sample over time and to update and refine the efficiency adjustments of physical capital stock.

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Appendix: International Standard Classification of Education 1997 (ISCED 97)

(copied from https://ec.europa.eu/eurostat/cache/metadata/Annexes/educ_uoe_h_esms_an2.htm on November 30, 2021)

__List of educational levels__

ISCED 0 Pre-primary level of education

Initial stage of organised instruction, designed primarily to introduce very young children to a school-type environment.

ISCED 1 Primary level of education
Programmes normally designed to give students a sound basic education in reading, writing and mathematics.

ISCED 2 Lower secondary level of education (2A, 2B, 2C)
The lower secondary level of education generally continues the basic programmes of the primary level, although teaching is typically more subject-focused, often employing more specialised teachers who conduct classes in their field of specialisation.
ISCED 2A Programmes designed to prepare students for direct access to level 3 in a sequence which would ultimately lead to tertiary education, that is, entrance to ISCED 3A or 3B.
ISCED 2B Programmes designed to prepare students for direct access to programmes at level 3C. ISCED 2C Programmes primarily designed for direct access to the labour market at the end of this level (sometimes referred to as 'terminal' programmes).

ISCED 3 Upper secondary level of education (3A, 3B, 3C)
The final stage of secondary education in most countries. Instruction is often more organised along subject- matter lines than at ISCED level 2 and teachers typically need to have a higher level, or more subject- specific, qualification that at ISCED 2. There are substantial differences in the typical duration of ISCED 3 programmes both across and between countries, typically ranging from 2 to 5 years of schooling.
ISCED 3A Programmes at level 3 designed to provide direct access to ISCED 5A. ISCED 3B Programmes at level 3 designed to provide direct access to ISCED 5B.
ISCED 3C Programmes at level 3 not designed to lead directly to ISCED 5A or 5B. Therefore, these programmes lead directly to labour market, ISCED 4 programmes or other ISCED 3 programmes.

ISCED 4 Post-secondary, non-tertiary education (4A, 4B, 4C)
These programmes straddle the boundary between upper secondary and post-secondary education from an international point of view, even though they might clearly be considered as upper secondary or post- secondary programmes in a national context. These programmes are often not significantly more advanced than programmes at ISCED 3 but they serve to broaden the knowledge of participants who have already completed a programme at level 3. The students are typically older than those in ISCED 3 programmes. They typically have a full-time equivalent duration of between 6 months and 2 years.

ISCED 4A Programmes at level 4, designed to provide direct access to ISCED 5A. ISCED 4B Programmes at level 4, designed to provide direct access to ISCED 5B.
ISCED 4C Programmes at level 4 not designed to lead directly to ISCED 5A or 5B. These programmes lead directly to labour market or other ISCED 4 programmes.

ISCED 5 First stage of tertiary education (5A, 5B)
Programmes with an educational content more advanced than those offered at levels 3 and 4. ISCED 5A Programmes that are largely theoretically based and are intended to provide sufficient qualifications for gaining entry into advanced research programmes and professions with high skills requirements. Duration categories: Medium: 3 to less than 5 years; Long: 5 to 6 years; Very long: More than 6 years.

ISCED 5B Programmes that are generally more practical/technical/occupationally specific than ISCED 5A programmes. Duration categories: Short: 2 to less than 3 years; 3 to less than 5 years; Long: 5 to 6 Years; Very long: More than 6 years.

ISCED 6 Second stage of tertiary education (leading to an advanced research qualification)
This level is reserved for tertiary programmes that lead to the award of an advanced research qualification. The programmes are devoted to advanced study and original research.