Quality Hours: Measuring Labor Input

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Abstract

We construct an aggregate labor input series from 1979 to adjust for changes in the experience and education levels of the workforce using the Current Population Survey's Outgoing Rotation Groups. We compare the cyclical behavior of labor input to aggregate hours – finding that labor input is about 11% less volatile over the business cycle and that the quality of the workforce is countercyclical. We show that the decrease in labor productivity beginning in 2004, the "productivity slowdown," is understated by 23 percentage points when using aggregate hours instead of labor input to calculate productivity, as compared to the 1990-2003 growth rate. Moreover, 70% of the average quarterly growth rate of labor productivity can be attributed to increases in education and experience since 2004.

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1 Introduction

Not all hours are created equal. In this paper we present a method for adjusting aggregate hours to account for changes in the quality of hours worked. Average human capital has rapidly increased since 1980 as better educated cohorts enter the workforce and the baby boomers continue to work and gather experience. The neoclassical production function, when using hours in place of labor input, treats all hours as equal, and so measures of growth and productivity can be clouded by changes in the education and experience level of the workforce. In order to account for these changes in the quality of labor provided, we use data on individual workers from the Current Population Survey's Outgoing Rotation Groups to construct a measure of labor input. We scale each individual's hours worked by a weight, created from hourly wages, that reflects education-experience level and an individual residual to measure relative labor input.

We show that the cyclical behavior of labor input differs from aggregate hours: labor input is less volatile and has a slightly smaller contemporaneous correlation with real gross domestic product. Further, the measured average annual growth rate of labor productivity differs substantially when using labor input instead of aggregate hours. The average annual growth rate of labor productivity since 2004 is 0.75% when using aggregate hours, whereas labor productivity measured using labor input has an average growth rate of only 0.22%, implying that 70% of the growth of labor productivity since 2004 has been through an increase in education and experience. That is, the "productivity slowdown" is more severe when using labor input compared to aggregate hours, the decline is understated by 23 percentage points. Similarly, when using labor input instead of aggregate hours, the annual growth rate of total factor productivity (TFP) decreases from 0.63 to 0.16, implying that 75% of the growth in TFP since 1979 can be explained by increases in the quality of the workforce. We calculate the Solow residual using both our measures of labor input and aggregate hours and find that the cyclical component of the output residual remains almost unchanged. The autocorrelation of the Solow residual drops from 0.96 to 0.94 when using labor input and the standard deviation of the error component is unchanged at 0.007. Overall, accounting for changes in the quality if the workforce has a large effect on the trend of productivity but a rather small effect on the cyclical component of productivity.

With respect to Real Business Cycle (RBC) models for the economy, the volatility of labor input in these models is lower than that of aggregate hours in data from the U.S., see for example Hall (1997) and Christiano and Eichenbaum (1992), spurring the need to either reevaluate the model or the data. Several adjustments for changes in the quality of hours of work have been suggested in the past. Jorgenson et al. (1987), Hansen (1993), and Denison (1957) create labor input series by weighting hours by earnings at broad age-sex groups. Although this does adjust hours for quality across age-sex groups, it does not adjust for within group heterogeneity. Kydland and Prescott (1993) attempt to solve this problem by using the Panel Study of Income Dynamics (PSID) to weight hours at the individual level. The unit of time across these proposed series varies from yearly (Jorgenson et al., 1987; Denison, 1957; Kydland and Prescott, 1993), to monthly (Hansen, 1993) thus comparing the cyclical behavior across the different series is difficult. The benefit of using the Current Population Survey is that hours can be weighted at the individual level and the resulting labor input series is monthly. The series can be updated tin a timely manner and aggregated to any level for use in further analysis - thus combining the best of all current measures of labor input.

Recent literature commenting on the volatility of key economic series, has come to the consensus that there has been a significant drop in the volatility of these series in the post-war economy, typically citing 1984 as the turing point.[1] These papers focus on aggregate hours instead of compositionally adjusted series for labor input; however, the series proposed in this paper does not lend itself well to studying the post 1984 reduction in volatility since it can only be constructed beginning in 1979.

2 Measuring Labor Input

In this section we present a model of labor input and estimate labor input using data from the Current Population Survey Outgoing Rotation Group since January 1979 for private and government workers. The data include information about an individual's usual weekly hours worked in the previous month, hourly earnings, education and other individual characteristics. Details of the data processing can be found in Appendix A.

2.1 Model

In order to account for differences in worker's productivity, we start start by modeling worker $i's$ labor input at time t, l_{it}, as:

$$l_{it} = \gamma_i h_{it}. \tag{1}$$

[1]See for example Stock and Watson (2003), Hall (2007), Galí and van Rens (2008) and cites there within.

where h_{it} is hours worked and γ_i is the worker's individual productivity of an hour. The aggregate labor input at time t is

$$\begin{aligned} L_t &= \sum_i l_{it} \\ &= \sum_i \gamma_i h_{it}. \end{aligned} \tag{2}$$

We model aggregate output at time t, Y_t, as a Cobb-Douglas production function with two inputs: labor input, L_t and capital, K_t. The production function is given by:

$$Y_t = z_t K_t^{\alpha} L_t^{1-\alpha} \tag{3}$$

where z_t is an aggregate shock at time t and α is capital's share of output. Assuming markets are competitive, worker i's hourly wage is given by his marginal product of output. The natural log of worker i's wage is:

$$\ln w_{it} = \ln \frac{\partial Y_t}{\partial h_{it}} = \ln \left[(1-\alpha) z_t K_t^{\alpha} L_t^{-\alpha} \right] + \ln \gamma_i. \tag{4}$$

Notice that the first part of the right hand side of Equation 4 is common to all workers and can be interpreted as the aggregate labor market conditions at time t, and the second part of the right hand side of Equation 4 is the component of interest.

2.2 Empirical Specification

Ultimately, we are after estimating a reduced form version of Equation 4 to get an estimate of γ_i. Using the estimate of the worker's individual productivity, $\hat{\gamma}_i$, we can estimate labor input at time t using Equation 2. Our reduced form model for a worker's wage is as follows:

$$\ln w_{it} = \ln A_t + \ln \gamma_i + \nu_i \tag{5}$$

where A_t are the aggregate labor market conditions at time t and ν_i are individual demographic characteristics. To account for the aggregate labor market conditions we include time fixed effects which we allow to vary at the industry level, δ_{tj}, where j is one of 14 industries specified in Appendix A.

We assume that the individual demographic characteristics are observable characteristics of the worker that may affect his wage but not the productivity of an hour of work. Specifically, we assume that ν_i is composed of race, sex and marital status:

$$\nu_i = \alpha_1 \text{male}_i + \alpha_2 \text{hisp}_i + \alpha_3 + \text{black}_i + \alpha_4 \text{married}_i \tag{6}$$

where male_i, hisp_i, black_i, and married_i are dummies for if the worker is male, hispanic, black or married. The assumption that these characteristics do not affect the labor input of the worker, and that we will ultimately not weight hours by these characteristics warrants some discussion. Ideally we would like to give more weight to more productive individuals; however, differences in wage reflected by, for example sex, may not reflect differences in productivity of the individual but instead an occupational choice.[2] Consequently, if hours are weighted by sex, then men and women within the same occupation whose labor input may be identical will have different weights. Similarly, we do not weight hours by race since difference in wages across race may be a reflection of discrimination and not differences in labor input. This assumption stands in contrast to earlier work by Hansen (1993) and Jorgenson et al. (1987) who weight hours by demographic characteristics.

As noted by Kydland and Prescott (1993) however, wages are cyclical and may be a noisy signal of productivity if a worker's wage is only observed once. For example, a college educated worker with 10 years of experience may have a different wage depending on whether he is observed during a boom or a recession. Therefore, weighting hours by raw wages is problematic since wages may be distorted by when a worker is observed. To avoid such distortions, we include time by industry fixed effects into our reduced form specification of the natural-log wage.

We choose the weight to be composed of education, experience and an unobservable component ϕ_i, thus our specification for the parameter of interest, γ_i is:

$$\ln \gamma_i = \sum_k \beta_k \mathbb{1}\{edu_i = E_k\} + \beta_5 exp_i + \beta_6 exp_i^2 + \beta_7 exp_i^3 + \beta_8 exp_i^4 + \phi_i \tag{7}$$

where $\mathbb{1}\{edu_i = E_k\}$ is an indicator function that takes on the value 1 if a worker's education is in one of 5 categories: high school drop out (HSD), high school graduate (HSG), some college (SMC), college graduate (CLG), and greater than college (GTC) such that

[2]For example, Blau et al. (2013) find that there still exist significant segregation of employment for men and women across occupations and Blau and Kahn (2017) show that about one third of the gender wage gap can be explained by differences in the occupational choices of men and women.

$E_j \in \{HSD, HSG, SMC, CLG, GTC\}$. Our final empirical specification of the wage is:

$$\begin{aligned}\ln w_{ijt} &= \delta_{tj} + \alpha_1 \text{male}_i + \alpha_2 \text{hisp}_i + \alpha_3 + \text{black}_i + \alpha_4 \text{married}_i \\ &+ \sum_k \beta_k \mathbb{1}\{edu_i = E_k\} + \beta_5 exp_i + \beta_6 exp_i^2 + \beta_7 exp_i^3 + \beta_8 exp_i^4 + \varepsilon_{ijt}\end{aligned} \tag{8}$$

Using the estimated coefficients from Equation 8 the estimate of worker i's weight is:

$$\hat{\gamma}_i = \exp\left(\sum_k \hat{\beta}_k \mathbb{1}\{edu_i = E_k\} + \hat{\beta}_5 exp_i + \hat{\beta}_6 exp_i^2 + \hat{\beta}_7 exp_i^3 + \hat{\beta}_8 exp_i^4 + \hat{\phi}_i\right). \tag{9}$$

The individual component, $\hat{\phi}_i$, is the within industry-time normalized regression residual from Equation 8:

$$\hat{\phi}_i = \hat{\varepsilon}_{ijt} - \frac{1}{N_{jt}} \sum_i \hat{\varepsilon}_{ijt} \tag{10}$$

where N_{jt} is the number of workers in industry j at time t. The weight is time invariant and workers with identical observable characteristics will have almost identical weights over time. Only the unobservable characteristics differ across observably identical workers and therefore their weight will not be identical. However, more educated workers or workers with more experience will be weighted higher than their less educated or experienced counterparts in every year.

3 Findings

The standard measure of aggregate monthly hours calculated from the CPS is:

$$H_t = \sum_i (4.17 * h_{it})(orgwt_{it}). \tag{11}$$

where h_{it} are the usual weekly hours reported by person i in year t and $orgwt_{it}$ is the Outgoing Rotation Group weight for person i at time t. Weekly hours are multiplied by 4.17 to get usual monthly hours. Using the estimated weight, Equation 9, aggregate monthly labor input is:

$$L_t = \sum_i (4.17 * \hat{\gamma}_i * h_{it})(orgwt_{it}) \tag{12}$$

Given the measure of labor input, we can find a summary statistic of the quality of the employed labor force by dividing labor input by aggregate hours. We define this statistic as workforce quality:

$$WQ_t = \frac{L_t}{H_t} \tag{13}$$

Workforce quality tracks changes in the average labor input per hour worked. In this section we analyze the sectoral and cyclical behaviors of aggregate hours, labor input, workforce quality as well as labor productivity measured using both aggregate hours (Y_t/H_t) and labor input (Y_t/L_t).

3.1 Labor Input

Figure 1 plots seasonally adjusted labor input and aggregate hours derived from the CPS as well as the hours series from the Current Employment Statistics (CES) for comparison. As the units of the labor input series is not the same as hours from the CPS or CES, the series are indexed to January 1979. The standard measure of hours from the CPS and hours reported by the Bureau of Labor Statistics in the CES track each other closely. Labor input has a larger trend and diverges from the standard measure of hours.

Figure 1: Labor Input and Hours

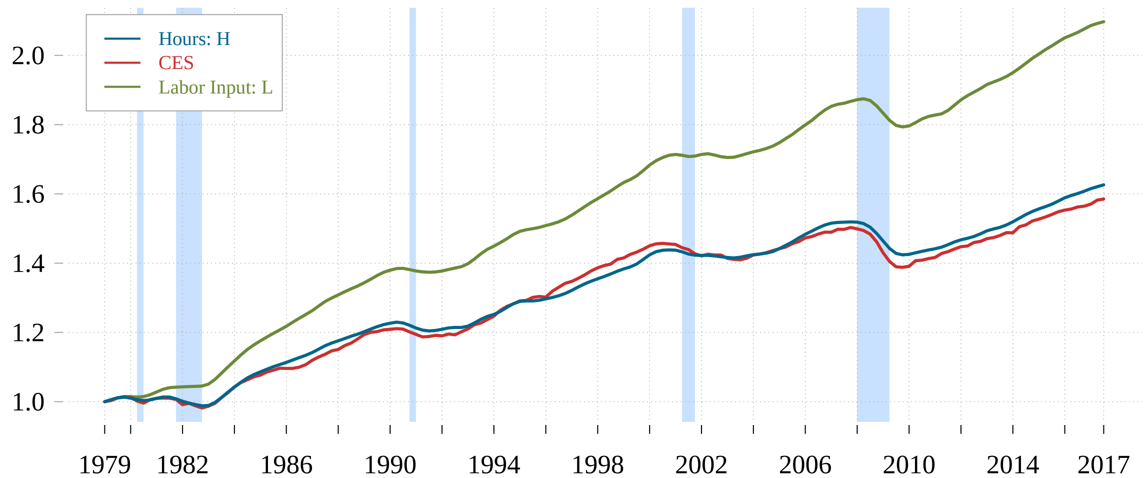


Table 1: Yearly Growth Rates of Hours and Labor Input

Years	Hours	Labor Input
1980-2016	1.27	1.97
1983-1990	2.66	3.58
1992-2000	1.93	2.38
2002-2007	1.00	1.42
2010-2016	1.51	1.90

Table 2: U.S. 1979Q1–2016Q4: Selected Moments

	Standard Deviation	Cross Correlation of Real Gross Domestic Product With								
		x_{t-4}	x_{t-3}	x_{t-2}	x_{t-1}	x_t	x_{t+1}	x_{t+2}	x_{t+3}	x_{t+4}
Real Gross Domestic Product	1.29	0.25	0.46	0.68	0.87	1.00	0.87	0.68	0.46	0.25
Employment	0.99	0.02	0.22	0.43	0.65	0.80	0.88	0.85	0.76	0.62
Aggregate Hours	1.27	0.03	0.22	0.44	0.66	0.82	0.89	0.86	0.76	0.61
Hours Per Worker	0.33	0.04	0.21	0.40	0.59	0.73	0.79	0.75	0.64	0.47
Labor Input	1.13	0.01	0.19	0.40	0.61	0.77	0.85	0.83	0.75	0.62
Labor Input Per Worker	0.31	−0.04	0.01	0.08	0.17	0.26	0.30	0.33	0.32	0.28
Workforce Quality	0.27	−0.10	−0.25	−0.41	−0.54	−0.60	−0.62	−0.55	−0.41	−0.26
GDP/Hour	0.77	0.37	0.40	0.39	0.36	0.31	−0.02	−0.29	−0.49	−0.59
GDP/Labor Input	0.83	0.38	0.45	0.50	0.51	0.49	0.18	−0.09	−0.32	−0.47

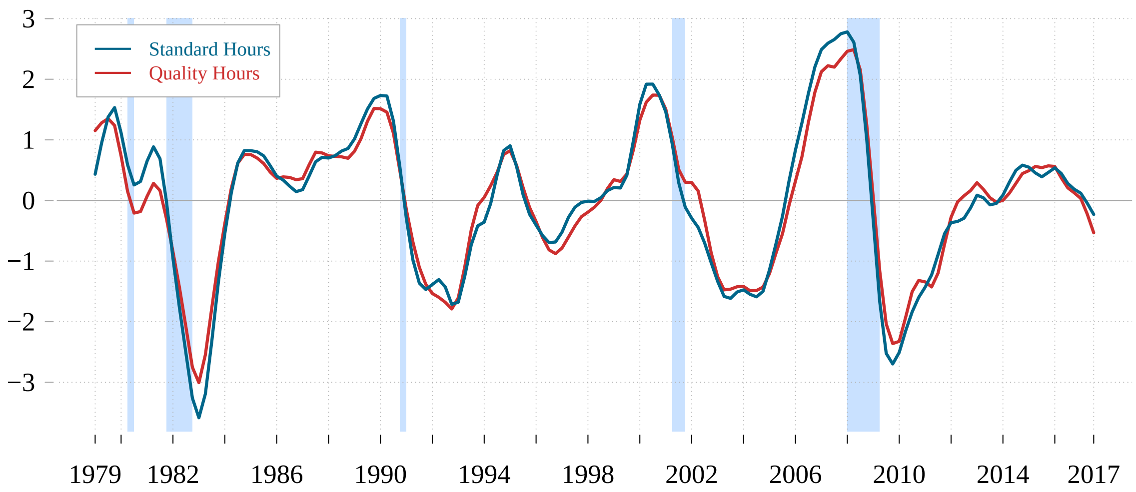
Table 1 shows the average yearly growth rate of the labor input and aggregate hours over the entire sample and between each recession. Over all, the yearly growth rate of labor input is 0.5 percentage points higher than that of aggregate hours. The growth rate of both series display similar trends, with high growth rates from the early 1980's until the 2001 recession, after which both growth rates fell by nearly 1 percentage point. After the great recession, both the growth rate of labor input and aggregate hours has increased, although not returned to their pre-2000 levels. The largest difference in growth rate was during 1983-1990, when the growth rate of labor input was 0.92 percentage points higher than that of aggregate hours. These differences in growth rates are driven by a rapid increase in the education and experience level of the workforce beginning in the 1980's.

As well as differences in secular trends, labor input and aggregate hours display differences in cyclical behavior. Statistics for comparing the cyclical behavior of the two series are created by logging and detrended the series using the Hodrick and Prescott (1997) filter. Table 2 shows the standard deviation and cross correlation of real gross domestic product (GDP) with labor input, aggregate hours and other labor market indicators. Labor input and aggregate hours lag the cycle; however, the contemporaneous correlation and first lag correlation of labor input with real GDP are less than those of aggregate hours. The contemporaneous correlations of aggregate hours and employment with real GDP are 0.82 and 0.80. The contemporaneous correlation of labor input with GDP falls to 0.77. These results are in line with Kydland and Prescott (1993), who find that the contemporaneous correlation of gross national product (GNP) with labor input is 0.75, in contrast to 0.8 for aggregate hours. These findings are contrary to Hansen (1993), who finds that the contemporaneous correlation of labor input with GNP is only slightly lower than that of aggregate hours.

The first column of Table 2 shows also that labor input is less volatile than aggregate hours.

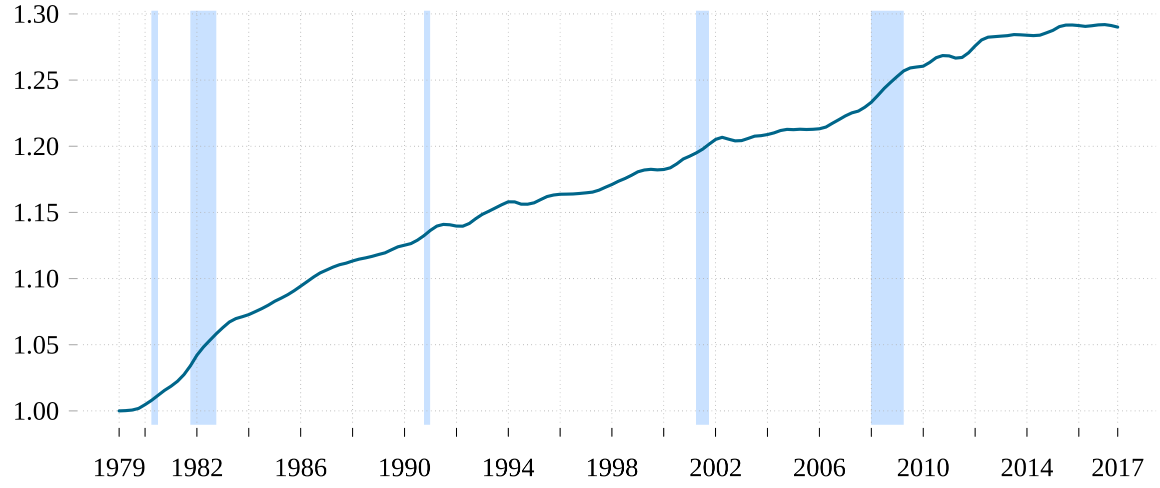
Figure 2 plots the percent deviations from trend of aggregate hours and labor input. The standard deviation of labor input is 1.13 whereas the that of aggregate hours is 1.27, which constitutes an 11% decrease in volatility. This decrease is between those found in Hansen (1993) and Kydland and Prescott (1993), who find a decrease in volatility of 5% and 23%, respectively. However, the volatility of aggregate hours is much higher in previous papers since the data used ends in the mid to late 1980's before the beginning of the great moderation. As mentioned by Hansen (1993) the difference in results about volatility of labor input versus aggregate hours (from those presented here and in Kydland and Prescott (1993)) may be driven by the unit of observation. Here, hours are weighted at the individual level whereas Hansen (1993) weights hours at relatively broad age-sex subgroups. The contrasting results from weights constructed from individual data versus broader groups suggest that the cyclical properties of hours among workers within sex-age groups differ substantially.

Figure 2: Percent Deviation from Trend: Hours



Additionally, Table 2 contains statistics about hours per worker and labor input per worker. Although the two series have similar standard deviations, their contemporaneous correlations with GDP differ. Hours per worker is highly correlated with GDP, 0.73, whereas labor input per worker has a contemporaneous correlation with GDP of 0.26. These differences may arise from the types of workers laid off during recessions. If, for example, workers with the lowest labor input are laid off first, labor input per worker would be less positively correlated with GDP over the business cycle.

Figure 3: Quality of the Employed Workforce



3.2 Workforce Quality

Given the measure of labor input, we derive a summary statistic of the quality of the labor market by dividing labor input by aggregate hours, Equation 13. Workforce quality shows changes in the average labor input per hour; Figure 3 plots the series. The figure illustrates that the quality of hours worked has risen gradually since 1979. This is consistent with the rise in the average level of experience and education of the labor force over the past 35 years. The figure shows that the quality of the employed workforce has risen about 30% since 1979.

Figure 4: Percent Standard Deviations from Trend: Labor Quality

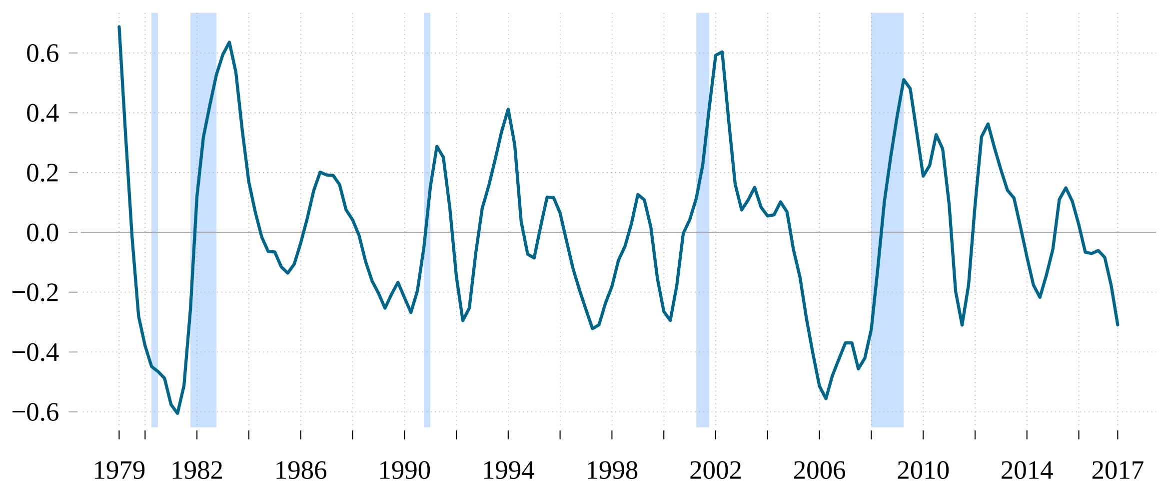


Figure 4 plots the percent standard deviations from trend of workforce quality. The figure reveals that the quality of the employed workforce is countercyclical and has a slight phase shift in the direction of lagging the cycle. Table 2 gives the cross correlations of GDP with workforce quality. The contemporaneous correlation between the quality of the labor force and real GNP is -0.6. The rise of labor quality during recessions suggests that less educated and experienced workers lose their jobs first and the fall during booms suggests they become rehired last. The rise in the quality hours measures during recessions can also be attributed to how workers and firms sort over the business cycle as modeled in Lise and Robin (2017). The counter-cyclical behavior of workforce quality is in line with the large decrease in the contemporaneous correlation of labor input per worker with GDP.

3.3 Labor Productivity

Figure 5 plots labor productivity using labor input and aggregate hours. Both series are indexed to January 1979. It is well known that the growth of labor productivity, measured as GDP per aggregate hours, has fallen since the mid 2000's, see Byrne et al. (2016) for example. But as Figure 5 demonstrates, labor productivity measured using labor input has grown even substantially more slowly. In fact, GDP per labor input was nearly flat between 1980-1990 and 2004-2016. Table 3 gives the annualized growth rate of quarterly labor productivity for both measures. Over the entire sample GDP per hour grew at an annualized rate of 1.32 percent whereas GDP per labor input grew at an annualized rate of 0.63 percent per year. Furthermore, Table 3 shows the average annualized growth rates for 3 different time periods. First, from 1979 to 1989 the average annual growth rate of GDP per hour was 1.14%, and the average annual growth rate of GDP per labor input was 0.05%. This implies that the majority of productivity growth from 1979 to 1989 came from increases in education and experience of the workforce. Second, the average annual growth rate from 1990 to 2003 was nearly 2% for GDP per hour and 1.47% for GDP per labor input. Although the average education and experience of the workforce continued to increase over this period, a substantial part of the increase in labor productivity is attributed to other factors. Lastly, when looking at the most recent time period, 2004 to 2016, the average annual growth rate of both measures has decreased. The annual growth rate of GDP per hour has fallen by 62%, from 2% to 0.75% and the annual growth rate of GDP per labor input has fallen by 85% from 1.47% to 0.22%. Again, the low growth rate of GDP per labor input implies that increases in education and experience of the workforce account for about 70% of the growth in productivity since 2004.

Figure 5: Labor Productivity

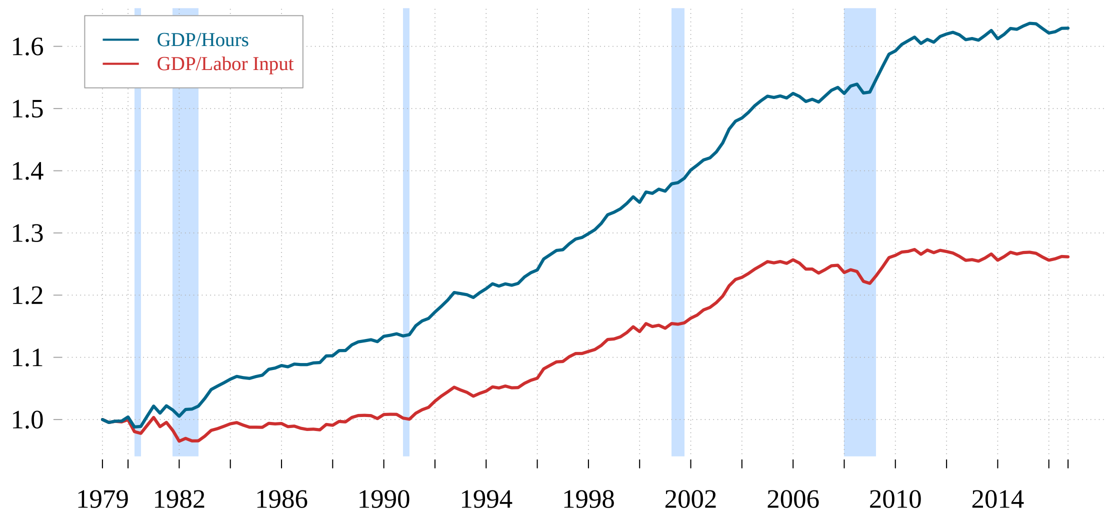


Table 3: Annualized Growth Rate of Quarterly Labor Productivity

Years	GDP/Hours	GDP/Labor Input
1979-2016	1.32	0.63
1979-1989	1.14	0.05
1990-2003	1.99	1.47
2004-2016	0.75	0.22

We argue that both GDP per hour and GDP per labor input are important measures for assessing economic growth. Since GDP per hour includes all factors that make workers more productive, it gives a general sense of how productive the workforce is, and growth in GDP per hour is what ultimately leads to economic growth. On the other hand, if one is interested in what may be driving an increase in productivity, GDP per hour alone falls short. GDP per labor input is constructed such that hours of workers with the same years of eduction and experience are weighted the same across time. Therefore, changes in GDP per labor input can be attributed to factors other than changes in experience and education. Together, GDP per hour and GDP per labor input can give some insights into what factors are driving increases in labor productivity.

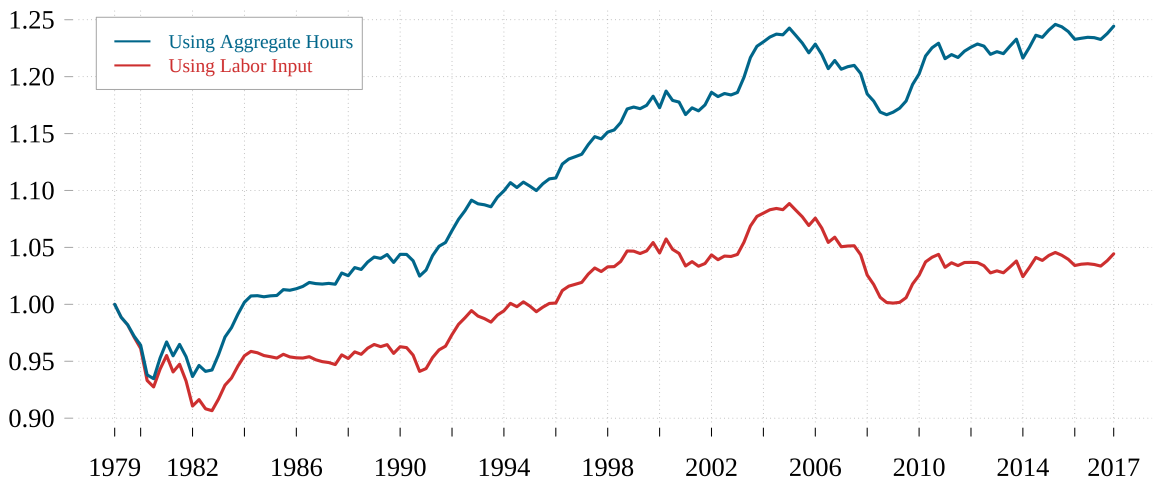
Table 2 shows the cyclical behavior of GDP per hour and GDP per labor input. Both series lead the cycle, however GDP per labor input has a higher contemporaneous correlation with GDP, 0.49, than GDP per hour, 0.31. This stands in contrast to Galí and van Rens (2008) who argue that the pro-cyclicality of labor productivity with output has decreases substantially post-1984. Similarly the standard deviation the cyclical component of GDP per labor input, 0.83, is higher than that of GDP per hour, 0.77.

3.4 Total Factor Productivity

Given the Cobb-Douglas structure in aggregate production, Equation 3, and our measure of labor input, we can calculate total factor productivity (TFP), z_t, as the Solow residual. We measure the capital stock and capital's share of output, α, as described in Gomme and Rupert (2007). The average annual capital share of output since 1979 is $\alpha = 0.312$ and the measurement of the real capital stock from 1979 is plotted in Figure A.1 in Appendix A.

Figure 6 shows the normalized total factor productivity since 1979 calculated using both aggregate hours and labor input. The result is similar to labor productivity. Table 4 shows that the average annual growth rate of TFP since 1979 is 0.63 when measured using aggregate hours and 0.16 when measured using labor input.

Figure 6: Total Factor Productivity



Since our measure of labor input is slightly less volatile than aggregate hours over the business cycle, TFP must capture more of the volatility in output. To see the extent to which TFP volatility increases when using labor input instead of aggregate hours, we run the following AR(1) process on the estimated Solow residuals:

$$\ln z_t = \rho_1 + \rho_2 \ln z_{t-1} + \rho_3 t + \epsilon_t \tag{14}$$

using both the residuals when using labor input and aggregate hours.

Table 4: Yearly Growth Rate of Total Factor Productivity

	Measured Using	
Years	Hours	Labor Input
1979-2016	0.63	0.16
1979-1989	0.56	-0.22
1990-2003	1.07	0.71
2004-2016	0.21	-0.14

Table 5 shows the estimated coefficients from Equation 14 using the residuals from labor input and aggregate hours. Since labor input is less cyclical, the variance of the error terms is slightly lower. However, the estimate is still in line with what authors have used in the literature to calibrate models. The autocorrelation term of the residual also drops when using labor input, but this drop is not statistically significant. In total, including labor input into the production function instead of aggregate hours has a large and significant effect on measured growth of productivity. The effects on the cyclical component of output, however, are almost unchanged.

Table 5: Solow Residual Regressions

	Measured Using	
Years	Hours	Labor Input
Lag	0.964	0.946
	(0.022)	(0.022)
Constant	-0.388	-0.599
	(0.241)	(0.256)
Time ($\times 10^{-3}$)	0.006	0.005
	(0.005)	(0.002)
SD(ϵ_t)	0.0072	0.0073

4 Alternative Measures

For completeness, in this section we compare our measure of labor input to commonly used quantity indices. We use our method of weighting hours at the individual level and compute the Laspeyres, Paasche and Fisher quantity indices.

4.1 Laspeyres Quantity Index

Our measure of labor input is most closely related to the Laspeyres quantity index. Diewert (1976) suggests the following calculation as the the Laspeyres quantity index:

$$S_t^Q = \frac{\sum_i q_{it} p_{i0}}{\sum_i q_{i0} p_{i0}} \tag{15}$$

where q_{it} and p_{it} are the quantity and price of good i at time t. Note that the Laspeyres quantity index requires only information on prices at time 0 but quantities in all time periods. Relating back to our measure of Labor Input, quantities q_{it} are equivalent to hours worked by individual i at time t, h_{it}.

Our measure differs slightly from the Laspeyres quantity index in its measure of prices, p_{i0}. While the Laspeyres quantity index uses period-0 prices to weight quantities, our measure of labor input uses a measure of the average relative price of individuals over the entire sample, $\hat{\gamma}_i$. For comparison we calculate the standard Laspeyres quantity index as follows:

$$S_t^Q = \frac{\sum_g \hat{\gamma}_{g0} h_{gt}}{\sum_j \hat{\gamma}_{g0} h_{g0}} \tag{16}$$

where $t = 0$ is January of 1979. Since we do not observe the same individual over the entire sample, g indexes education-experience groups where education can fall into one of the five categories defined above and experience is binned into single year categories. The estimated price for each group $\hat{\gamma}_{g0}$ as before,

$$\hat{\gamma}_{g0} = \exp\left(\sum_k \hat{\beta}_k \mathbb{1}\{edu_{g0} = E_k\} + \hat{\beta}_5 exp_{g0} + \hat{\beta}_6 exp_{g0}^2 + \hat{\beta}_7 exp_{g0}^3 + \hat{\beta}_8 exp_{g0}^4\right) \tag{17}$$

where the coefficients on education and experience are estimated from wages using only observations from January 1979, i.e. $t = 0$. The regression on wages is as follows:

$$\begin{aligned} \ln w_{ij0} &= \delta_j + \alpha_1 \text{male}_i + \alpha_2 \text{hisp}_i + \alpha_3 + \text{black}_i + \alpha_4 \text{married}_i \\ &\quad + \sum_k \beta_k \mathbb{1}\{edu_i = E_k\} + \beta_5 exp_i + \beta_6 exp_i^2 + \beta_7 exp_i^3 + \beta_8 exp_i^4 + \varepsilon_{ij} \end{aligned} \tag{18}$$

where δ_j are industry fixed effects. The main difference between the estimated prices $\hat{\gamma}_{g0}$ from Equation 17 and prices used in our measure of labor input, $\hat{\gamma}_i$ from Equation 9, is the inclusion of the regression residual ϕ_i which makes our labor input price vary at the individual level instead of the group level.

4.2 Paasche Quantity Index

Diewert (1976) suggests the following calculation as the Paasche quantity index:

$$P_t^Q = \frac{\sum_i q_{it} p_{it}}{\sum_i q_{i0} p_{it}} \tag{19}$$

where q_{it} and p_{it} are the quantity and price of good i at time t. The Paasche quantity index requires information about both prices and quantities in every time period. We estimate prices in every period by regressing log wages on education, experience, demographics and an industry fixed effect as in Equation 18. This gives an estimate on education and experience for every month since January 1979. Figure 7 shows the yearly average of the education coefficients over time. The figure indicates that most of the increase in the return to education occurred in the 1980's with college graduates earning about 80% more than high school dropouts and workers with more than sixteen years of education earning almost double that of high school dropouts since the mid 1990's. We use these coefficients, along with those on experience, to calculate an estimated price $\hat{\gamma}_{gt}$ for each education-experience group, g, for each time period, t as follows:

$$\hat{\gamma}_{gt} = \exp\left(\sum_k \hat{\beta}_k \mathbb{1}\{edu_{gt} = E_k\} + \hat{\beta}_5 exp_{gt} + \hat{\beta}_6 exp_{gt}^2 + \hat{\beta}_7 exp_{gt}^3 + \hat{\beta}_8 exp_{gt}^4\right) \tag{20}$$

We calculate the Paasche quantity index as:

$$P_t^Q = \frac{\sum_g \hat{\gamma}_{gt} h_{gt}}{\sum_g \hat{\gamma}_{gt} h_{g0}} \tag{21}$$

where h_{gt} are the aggregate hours of group g at time t.

Figure 8 plots the seasonally adjusted Paasche and Laspeyres quantity indices along with our measure of labor input and the Fisher quantity index defined as the geometric mean of the Paasche and Laspeyres indices:

$$F_t^Q = \sqrt{P_t \times S_t}. \tag{22}$$

All four series follow a similar pattern, having increased between 90 to 110 percent since 1979. Our measure of labor input has grown more than the alternative measures because the individual weight used in our measure includes the regression residual. It is well known that residual wage inequality has increased in the U.S. since the 1980's therefore, by weighting at the individual level, i.e. including the regression residual, accounts for the within education-experience group heterogeneity leading to a higher level of labor input.[3]

[3]See for example Autor et al. (2008) or Lemieux (2006)

Figure 7: Education Coefficients

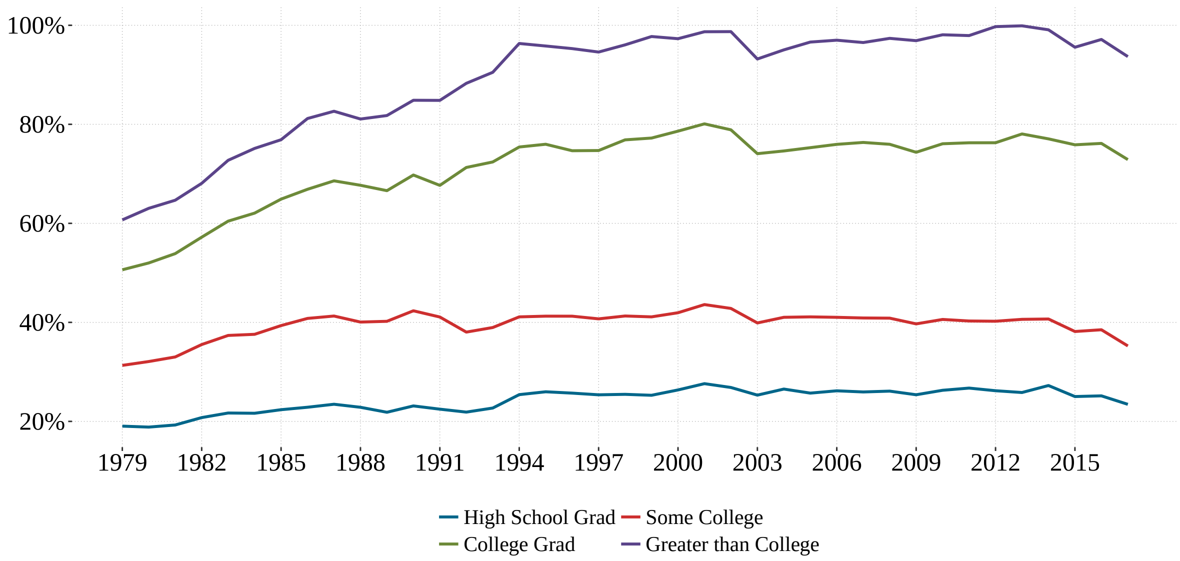
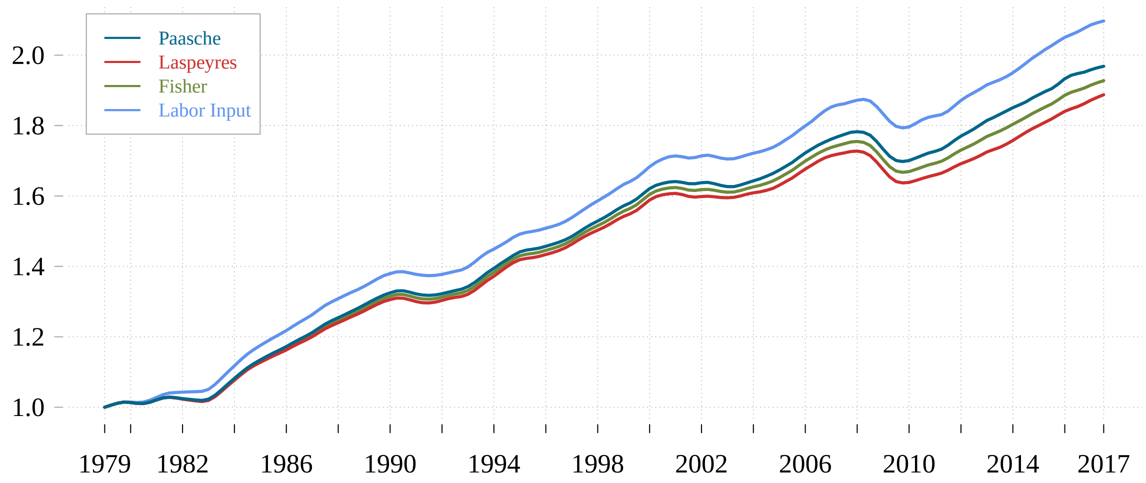


Figure 8: Indicies



4.3 Chain-Weighted Indices

We construct the the chain weighted Paasche quantity and Laspeyres quantity index as follows:

$$CS_t^Q = \frac{\sum_g \hat{\gamma}_{g0} h_{g1}}{\sum_j \hat{\gamma}_{g0} h_{g0}} \times \frac{\sum_g \hat{\gamma}_{g1} h_{g2}}{\sum_j \hat{\gamma}_{g1} h_{g1}} \times \cdots \times \frac{\sum_g \hat{\gamma}_{gt-1} h_{gt}}{\sum_j \hat{\gamma}_{gt-1} h_{gt-1}} \tag{23}$$

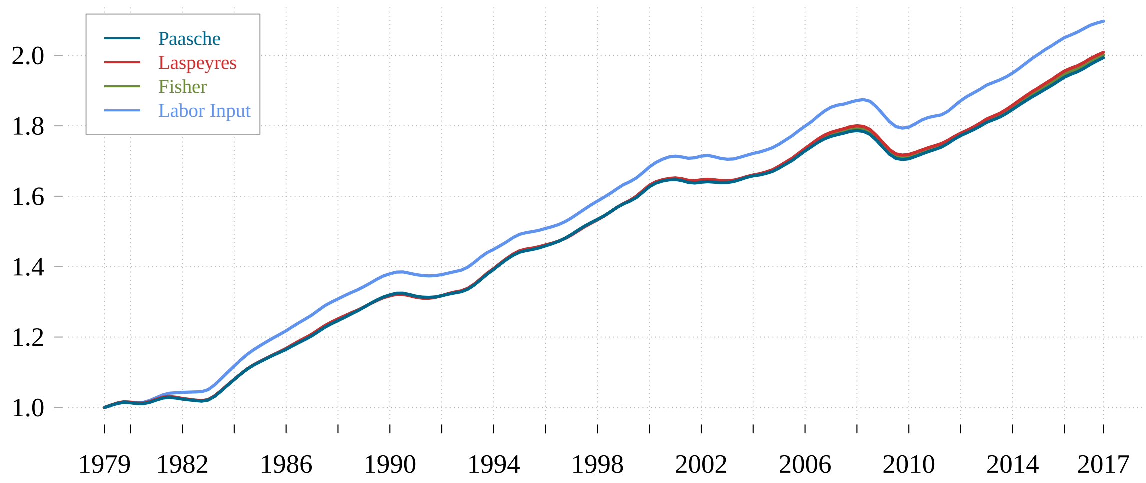
$$CP_t^Q = \frac{\sum_g \hat{\gamma}_{g1} h_{g1}}{\sum_g \hat{\gamma}_{g1} h_{g0}} \times \frac{\sum_g \hat{\gamma}_{g2} h_{g2}}{\sum_g \hat{\gamma}_{g2} h_{g1}} \times \cdots \times \frac{\sum_g \hat{\gamma}_{gt} h_{gt}}{\sum_g \hat{\gamma}_{gt} h_{gt-1}} \tag{24}$$

where $\hat{\gamma}_{gt}$ are calculated as in Equation 20 and h_{gt} are the aggregate hours of education-experience group g at time t. The chain weighted Fisher quantity index is:

$$CF_t^Q = \sqrt{CS_t^Q \times CP_t^Q}. \tag{25}$$

Figure 9 plots the seasonally adjusted Paasche, Laspeyres, and Fisher quantity index as well as our measure of labor input. Again the series show similar growth, increasing between 100 and 110% since 1979, in contrast to standard aggregate hours, that increased only 60% since 1979.

Figure 9: Chain Weighted Indices



5 Conclusion

We construct an aggregate labor input series since 1979 using the Current Population Survey. We model each individual's contribution to labor input as their hours worked times an individual weight. We use a Mincer-type regression of wages on education, experience, demographics and industry to estimate the average education and experience premium over the sample. Using the estimated education and experience premiums as well as the regression residual we construct the individualized weights. The series for labor input presented in this paper is a considerable improvement over past series: it is constructed from data on individuals at a monthly frequency and updated easily with the newest release of the CPS.

We show that labor input is less volatile over the business cycle and has a lower contemporaneous correlation with Gross Domestic Product (GDP) than aggregate hours. These results stem from the fact that workforce quality is countercyclical, i.e. less educated and less experienced workers leave employment first during recessions. We show that workforce quality, or the average labor input per hour of work, has increased by 30% since 1979. We calculate labor productivity as GDP per labor input and show that the average annual growth rate of labor productivity has decreased by 85% since 2004 in contrast to 62% when using GDP per hour as a measure of labor productivity. Comparing labor productivity measured using GDP per labor input and GDP per hour reveals that the increase in education and experience accounts for about 70% of growth in labor productivity since 2004, whereas increases in education and experience account for only 26% of growth in labor productivity between 1990 and 2003.

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A Data Appendix

A.1 Sample Selection and Data Cleaning

We use the Merged Outgoing Rotation Group files from the National Bureau of Economic Research (NBER).[4] We restrict the sample to private and government workers wage 16 or older. We construct a consistent education variable using the method described in Jaeger (1997) and compute experience as the maximum of zero and age minus education minus six.

We use the weekly wage variable provided by the NBER, *earnwke*, which includes overtime, tips and commissions. The variable is constructed from the census variable *a-werntp* from 1979 to 1993, *prernwa* from 1994 to 1997, and *pternwa* from 1998 onward. All top coded values are multiplied by 1.3. We use the usual hours worked variable provided by the NBER, *uhourse*, which is constructed from the census variable *a-uslhrs* from 1979 to 1993 and *peernhro* from 1994 onward. Between 1998 and 2002 there exist 823 observations which have a positive value for usual weekly hours and missing weekly earnings. For these observations we impute the weekly wage. In each year we regress log weekly earnings on a quartic in experience, dummy variables for the education groups, high school dropout, high school graduate, some college, college graduate, and greater than college, and dummy variables for sex, martial status, race, and state. For each year we replace the missing weekly earnings variable with the predicted weekly wage. We construct real hourly wages by dividing weekly earnings by usual hours per week and deflate using the Chain-type Personal Consumption Expenditures Price Index to deflate wages. We replace zeros with 0.01 and log real hourly wages.

We use the industry wage variable *dind* from 1979 to 2002 and *dind02* provided by the NBER for a consistent industry classification. We then construct 14 broad industries: agriculture and mining, construction, utilities, manufacturing, wholesale trade, retail trade, transportation and

[4] http://www.nber.org/cps/

warehousing, information, finance and real estate, professional and business services, education and health services, arts and entertainment, and government.

A.2 Removing Jumps in Series

Due to the 1994 redesign of the CPS, all aggregate hours and labor input series have a discontinuous jump up from December 1993 to January 1994. To remove this jump we first find the average change in each series from December to January for all year expect 1993-1994. We then multiply the first part of each series (January 1979 through December 1993) by a constant such that the change from December 1993 to January 1994 is equal to the average December-January jump of all other years. We implement this procedure on unfiltered, not seasonally adjusted data.

A.3 Seasonal Adjustment and HP Filtering

To seasonally adjust the aggregated series created from the CPS by decomposing the series into a trend, seasonal, and irregular component. The irregular component corrects sampling error.[5] Next we aggregate the seasonally adjusted series to a quarterly frequency and filter it into a trend and business cycle component using the Hodrick-Prescott filter with smoothing component $\lambda = 1600$.

A.4 Capital Stock

[5]See Tiller and Natale (2005) for details about including an irregular component into the decomposition. See Cleveland et al. (1990) for details about the decomposition.

Figure A.1: Real Capital Stock