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Abstract

Because labor quality changes over the business cycle, the cyclicalities of aggregate wages cannot reflect the true cyclical behavior of the price of labor inputs. To control for changes in labor quality, many researchers have examined the cyclical behavior of the price of labor inputs using microdata sets with mixed results. In this paper, I develop a hedonic pricing method to examine the cyclicalities of real wages and implement it using the *U.S. Current Population Survey* (CPS) data. The flexibility of the hedonic method and the large sample size of the CPS data make it possible to replicate and reconcile the results from a number of major studies on a single data set. I find that the lower the frequency of the data, the greater is the procyclicality of real wages. This pattern has not been documented and cannot be explained by current business cycle theories.

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1 Introduction

Despite an extensive empirical literature on the cyclical behavior of real wages over the past decades, researchers still have not reached a consensus on whether real wages are procyclical, countercyclical or acyclical. This series of studies began with Dunlop's (1938) and Tarshis's (1939) pioneering studies, in which real wages were found to be weakly procyclical or acyclical. Subsequent studies based on aggregate data sets also failed to find a strongly cyclical real wage.¹ Weakly procyclical real wages are problematic for Keynesian theory, because it assumes that employment moves along a stable labor demand curve, and hence that real wages are strongly countercyclical. Weakly procyclical real wages are also problematic for prototype real business cycle (RBC) models which emphasize technology shocks. Their predictions on the correlation and relative volatility between real wages and labor input are much higher than those found in the data.

Because the low skilled workers' share of working hours are procyclical,² the weak procyclicality of real wages may be an artifact of the aggregation process. In particular, the cyclical fluctuations in aggregate real wages are attenuated by fluctuations in labor quality. Since the early 1980s, many researchers have tried to control for changes in labor quality by using panel data sets.³ However, this work has not reached a consensus either. The studies using the Panel Study of Income Dynamics (PSID) have concluded that real wages are strongly procyclical and changes in labor quality have a significant effect on the cyclicity of real wages. In contrast, no unanimous conclusion has been reached from studies using the National Longitudinal Survey of Young Men (NLS). For example, Bils (1985) finds that real wages are strongly procyclical and changes in labor quality only have a minor effect

¹See Bodkin (1968), Neftci (1978), Sargent (1978), Geary and Kennan (1982), Summer and Silver (1989).

²For example, Kydland (1984) finds that less-educated workers' working hours decrease more than well-educated workers in recessions among prime age males in the United States. Mitchell (1985) *et. al.* find that the unemployment rate of young workers increases more than that of prime age male workers in recessions.

³See Bils (1985), Blank (1990), Hansen (1993), Keane *et al* (1989), Kydland and Prescott (1993), Solon *et al* (1994), Stockman (1983) and Wilson (1996).

(countercyclical) on the cyclicity of real wages. Keane, Moffitt and Runkle (1988) conclude that real wages are only weakly procyclical and changes in labor quality make aggregate real wages appear a bit more procyclical. Using two U.S. firm level data sets, Wilson (1996) finds that real wages are countercyclical. Obviously, the choice of data set is crucial in deriving the cyclicity of real wages. Because the panel studies are restricted to particular groups, one cannot discern which results reflect the cyclicity of real wages of the entire U.S. economy. Furthermore, annual frequency is used in panel studies while most macro economic business cycle models are generally calibrated to the quarterly frequency.

To examine the cyclicity of real wages of the entire U.S. economy, this paper uses a much larger data set, the U.S. Current Population Survey (CPS). Unlike earlier articles which emphasized changes in real wages at the individual level, I first construct an efficiency labor units series based on workers' personal characteristics and hours worked, and then investigate changes in the price of efficiency labor unit. The gains of adopting this approach are twofold. First, this method makes it possible to utilize both cross-section and panel data sets. This means the method is applicable to more countries, longer time frames and at more frequencies.⁴ Second, the correlation between labor input (total efficiency labor units) and its price as well as their relative variability can be examined. So the results are directly comparable with the predictions of most theoretical business cycle models.

The most striking finding of this paper is that the cyclical properties of the key variables in the quarterly data markedly differ from their annual counterparts. In the annual data, as in previous studies using the PSID data, real wages are strongly procyclical and changes in labor quality bias the cyclicity of real aggregate hourly wages countercyclically. In the quarterly data, real wages are weakly procyclical and changes in labor quality only slightly attenuate the cyclicity of real aggregate hourly wages.

⁴The highest frequency of the CPS is monthly. Thus I can easily address the cyclicity of real wages at quarterly and annual level.

I also find that the correlation between labor input and its price decreases monotonically with the frequency of data used. That is, the higher the frequency, the less procyclical the price of labor becomes. In the aggregate data, the correlation between real hourly wages and total working hours for all nonagricultural production workers also decreases as the frequency of the data used increases. However, in the manufacturing sector, the correlation between real hourly wages and hours worked is not sensitive to the frequency of data used. Because most previous studies based on aggregate data focused on the manufacturing sector, and the panel data used in previous studies are only available at the annual level, the strong relationship between the cyclicity of real wages and the data frequency has not been documented.⁵ This strong procyclicality found in previous micro studies, at least partially, resulted from the use of annual data and the particular sample coverage.

This paper is organized as follows. The basic framework is described in section 2. The data sets used in this paper are discussed in section 3. The estimation results are reported and some comparison with previous studies are made in section 4. Section 5 concludes.

2 The Framework

I adopt a hedonic approach to address the potential problems resulting from changes in labor quality. Hedonic methods have been widely used in constructing quality adjusted price indices.⁶ Because the reason for constructing those price indices is related to the underlying issue *i.e.* quality changes over time, it is a natural extension to apply the hedonic method to construct a labor input price series.

This approach has several advantages: First, it can be applied to both cross-section and panel data. This means that one can examine the cyclicity of real wages on higher

⁵To my knowledge, only Abraham and Haltiwanger (1995) note that real wages are more procyclical in annual than in quarterly data. However, their results indicate that the difference between the annual and quarterly data is small.

⁶See Triplett (1986) for computer price index, Griloches (1971) for automobile price index and Cheshire (1995) for housing price index.

frequency data (quarterly or monthly), and in various countries. Second, instead of focusing on the relationship between real wages and the unemployment rate, labor input and its price are measured directly. Thus a direct measure of their correlation is available. Because this correlation is calibrated in most business cycle models, the results from this study are directly relevant for the calibration of these models. Third, based on a “corrected” measure of labor input, technology shocks in business cycles or the Solow residual, can be measured more accurately. Finally, one can investigate whether the fluctuations in labor quality mainly arise from workers moving in and out of employment or from employed workers changing working hours. This knowledge is useful to business cycle theorists when making decisions on whether they should focus on the intensive margin or extensive margin when introducing heterogeneity in the labor force.

In the hedonic framework, changes in labor quality are quantitative changes in characteristics that are related to worker productivity. Thus, a qualitative measure in a general setting can be converted to a quantitative measure. The usual Cobb-Douglas production function becomes

$$Q = AK^\alpha \left(\sum_i h_i l_i \right)^{1-\alpha} = AK^\alpha \left[\sum h_i F(X_i) \right]^{1-\alpha}$$

where l is homogeneous human capital, h_i is working hours of individual i , $F(\bullet)$ is an aggregator over the personal characteristics X that produce units of homogeneous human capital, Q is total production, A measures the technology level, and K is the capital stock. In this setting, labor input is defined as the product of l and h , called *EUS* hereafter for efficiency units of labor. The marginal productivity of individual i in period t is

$$MPL_{it} = (1 - \alpha) A_t K_t^\alpha \left[\sum h_{it} F(X_{it}) \right]^{-\alpha} F(X_i).$$

If the labor market is perfectly competitive, workers’ real wages would be equal to their marginal products MPL_{it} . Otherwise, workers are paid proportional their marginal prod-

ucts, that is $w_{it} = MPL_{it}/\mu_t$, where μ_t is a markup factor that may change over time and business cycles. In both cases, the wage equation can be written as:

$$w_{it} = \lambda_t l_{it} \tag{1}$$

where

$$\lambda_t = (1 - \alpha) A_t K_t^\alpha \left[\sum h_{it} F(X_{it}) \right]^{-\alpha}$$

in a perfect competitive market and

$$\lambda_t = (1 - \alpha) A_t K_t^\alpha \left[\sum h_{it} F(X_{it}) \right]^{-\alpha} / \mu_t$$

in an imperfectly competitive market. One can think of λ_t as the rental rate for one unit of efficiency labor input. I will call it *EUP* hereafter for efficiency unit price.

Equation (1) implies

$$\ln w_{it} = \ln \lambda_t + \ln l_{it} = \ln \lambda_t + \ln [F(X_{it})].$$

Since a semilogarithmic form is widely used in the earlier literature when researchers addressed the determination of wage rates (Heckman and Polachek 1974, Bils 1983, Solon *et al.* 1994) and in the hedonic price indices literature (Griliches 1971b), I also choose this form for the wage equation. This implies that:

$$\ln [F(X_{it})] = \ln l_{it} = \beta_0 + X_{it}\beta_1 + \epsilon_{it}$$

where X_i is a vector of personal characteristics, β_0 is a constant and ϵ_i is the unobserved human capital embodied in individual i , assumed to have a zero mean. One can view $F(X)$ as a simple production function of human capital. Real wages can then be decomposed into the product of the level of human capital and its rental rate.

$$\ln w_{it} = \ln \lambda_t + \beta_0 + X_{it}\beta_1 + \epsilon_{it} \tag{2}$$

and

$$\ln w_{it} - \beta_0 - X_{it}\beta_1 = \ln \lambda_t + \epsilon_{it}.$$

If β_0 and β_1 are known, then

$$\ln \lambda_t = \frac{1}{N_t} \sum_i (\ln w_{it} - \beta_0 - X_{it}\beta_1)$$

where N_t is the number of workers employed at time t . The task is to estimate the β s. By assuming that the β s are constant over time, one can normalize λ to one in the base period, and the estimated $\hat{\beta}$ s from the base period data can be utilized in constructing the *EUP* series.

$$\ln \hat{\lambda}_t = \frac{1}{N_t} \sum_i (\ln w_{it} - \hat{\beta}_0 - X_{it}\hat{\beta}_1) \quad (3)$$

where $\hat{\beta}$ is estimated from the base period data⁷. Once the price of efficiency labor units is defined, the difference between *EUP* and aggregate real hourly wages (*AHW*) can be easily seen from the following formula:

$$w_{at} = \frac{\sum_i w_{it} h_{it}}{\sum_i h_{it}} = \frac{\sum_i \lambda_t l_{it} h_{it}}{\sum_i h_{it}} = \lambda_t \frac{\sum_i l_{it} h_{it}}{\sum_i h_{it}}$$

where w_{at} is aggregate hourly wages in studies using aggregate data sets. Unless workers moving in and out of employment do not change the distribution of l over the business cycle or the correlation between l and h , the cyclical behavior of *AHW* will differ from that of *EUP*. This is the notion of composition bias. Therefore, fluctuations in $\frac{\sum_i l_{it} h_{it}}{\sum_i h_{it}}$ have to be considered if we are interested in the cyclical behavior of *EUP*, the price of the labor input.

To estimate the hedonic function, personal characteristics that are most relevant to a worker's productivity have to be specified. In this paper, the hedonic function is defined as:

$$\ln w_i = \beta_0 + \beta_1 Edu_i + \beta_2 Exp_i + \beta_3 ExpS_i + \beta_4 S_i + \beta_5 PT_i + \beta_6 South_i + \epsilon_i \quad (4)$$

⁷In the Appendix, I show that $\ln \hat{\lambda}_t$ is a consistent estimator of $\ln \lambda_t$ even in the case which $\hat{\beta}$ is an inconsistent estimator of β .

where Edu is the years of education, Exp is a worker's working experience equal age minus years of schooling minus 5. S is a gender dummy equal to one if a worker is a male⁸, $South$ is a regional dummy variable equal to one if a worker lives in the South⁹, $ExpS$ is experience squared, and PT is a part-time dummy equal to one if a worker works part-time¹⁰.

Because years of schooling and experience are two key factors that could influence a worker's productivity, they are included in the hedonic function. Experience squared is included to capture the depreciation of human capital as well as changes in the investment in human capital over the life cycle. Female workers generally accumulate less human capital than male workers with the same potential years of working experience, and their share has increased significantly over the past decades. Therefore, a gender dummy is added in the hedonic function in order to minimize the bias induced by changes in the employment share of female workers.

The other two variables included in the hedonic function are a part-time dummy and a dummy indicating residence in the South. Including those two variables raises some interesting issues. On average, part-time workers earn about 20 percent less than full-time workers. Based on the matched CPS data, I find that hourly wages of part-time workers decrease if they switch from part-time jobs to full-time jobs, implying that productivity of part-time workers is lower than full-time workers. Blank (1990b) also finds that the productivity of female part-time workers is lower than full-time workers.

The south dummy is used to capture the difference in price levels and the industry composition between the South and the North in the U.S. Because the emigration decision is dependent on economic conditions, the cyclical of real wages could be biased if the

⁸I have tried to include interactions between sex and experience, sex and experience squared and sex and education, and the results are very close to the ones where I only include one gender dummy.

⁹The results are insensitive to whether I only include one South dummy or include 8 regional dummies for the 9 U.S. census divisions. For parsimony, I include only the South dummy here.

¹⁰The results are robust to whether I interact the PT dummy with experience, experience squared or I include only the PT dummy.

regional composition of the labor force is not controlled for.

3 The Data

The primary data source for this research is drawn from 32 years of the March U.S. Current Population Survey (MCPS) from 1963 to 1994, and the Outgoing Rotation Groups of the Current Population Survey (ORG) from January 1979 to December 1993. The advantages of using the CPS data are as follows. First, the sample size is very large. The number of workers who report positive labor incomes in the MCPS varies from 57,732 in 1974 to 85,895 in 1980, while in Kydland and Prescott's (1993) PSID sample, the maximum number of observation is only 4474. Second, the monthly CPS data (ORG) offers me the possibility of examining the cyclical behavior of labor input and its price at a higher frequency, while the previous micro studies were limited to annual data. Moreover, the CPS consists of repeated single random samples over time representing the U.S. population in any year (or month). In contrast, most panel data sets are only random at the beginning of the sample period. Because individuals may leave the population through death or emigration and join the population through birth or immigration, the panel data set may not be representative of the total population throughout the panel period. Finally, the CPS covers all demographic groups while most panels cover only selected cohort.¹¹

In the MCPS, annual labor income refers to the year preceding the survey year. The sample period of labor income in this paper covers the 1975-1994 period¹². In the ORG, earnings data refers to the current job, giving us a sample that covers the January 1979 to December 1993 period. Labor incomes are deflated by the CPI deflator (1982-1984=100).¹³

¹¹PSID only has earning information on household heads and wives and the NLS young man data only covers young males.

¹²MCPS was available since 1963, but the usual weekly hours worked were not recorded for the 1963-1974 period. However, sensitivity analysis with respect to this choice is done in Section 4.2.

¹³The main reason of choosing CPI deflator instead of GNP deflator is that the seasonal unadjusted GNP deflator is not available, and the unadjusted deflator is needed in order to calculate real wages from unadjusted nominal wages. Real wages are slightly more procyclical when the CPI deflator is used. However,

Because I am interested in the cyclicity of real wages of the entire economy, I include all nonselfemployed workers¹⁴ who report positive labor earnings in the MCPS and who have worked in the previous week in the ORG in the current study.¹⁵ Furthermore, the March Supplement Weight (the Earning Weight) is used in the MCPS (ORG) in order to construct aggregate measures of labor incomes and labor input.

Annual labor income consists of wage and salary income in the MCPS. Hourly wages of each individual are defined as the ratio of annual labor income to annual working hours. Aggregate hourly wages are defined as the ratio of total annual labor income to total annual working hours¹⁶. In the ORG, usual hourly wages on the current job are used as a proxy of the hourly wage in the current month for hourly workers.¹⁷ For salary workers, their hourly wages in the current month are defined as their usual weekly earnings divided by their usual weekly working hours. Hourly wages for those who worked in the last week but did not report earnings are imputed based on their personal characteristics.¹⁸

Finally, labor income is top coded in both the MCPS and the ORG, and the top value changes over time.¹⁹ A common practice is to multiply the top code value by 1.33 (Juhn, Murphy and Pierce 1993). Because both the wage distribution and the top code value change

the main quantitative results are robust to the choice of deflator.

¹⁴The rationale for including only nonselfemployed workers in this study is that the earnings data for selfemployed workers are not available in the ORG and a significant fraction of their earnings are negative in the MCPS.

¹⁵To test the sensitivity of the results to the sample selection criteria, I also examine the cyclicity of real wages of private nonagricultural workers in Section 4.2.

¹⁶For the 1963-1974 period, an imputation method is used to calculate annual hours worked. This method is described in the Appendix.

¹⁷Approximately 58 percent of employed workers are paid hourly over this 15 years period.

¹⁸Approximately 16 percent of the respondents who worked for pay in the last week did not report a wage. Moreover, this figure decreased to 10 percent in the third quarter of 1985 and returned to 16 percent in the second quarter of 1987. To impute the hourly wages, I first regress hourly wages on the personal characteristics defined in Section 2 for those whose wage data were available. The hourly wages of those whose wages were not reported are simply predicted based on these regressions.

¹⁹For the annual labor income, the top value was \$99999 from 1964 to 1967; the top value was \$50000 from 1968 to 1981; the top value was \$75000 from 1982 to 1984; the top value was \$99999 from 1985 to 1988; the top value was \$199998 from 1989 to 1995. For weekly earning, the top value was \$999 before 1985 and was \$1923 later on, the hourly earning is top coded at \$99.99 in most years and at \$99 for some years.

over time, this method introduces biases in the measurement of aggregate labor income. To address this problem, I first run a censored regression for each period (year or quarter), estimate the mean of the log annual labor income (hourly wages in the ORG), and multiply the earnings of the top coded observations by a constant to make the sample mean match the mean estimated from the censored regression.²⁰ There is no top coding in the 1988. Therefore, I use this year as the base year for the hedonic function.²¹

4 Estimation Results

4.1 Cyclicity of Real Hourly Wages

Following the tradition of theoretical business cycle models, I focus on the correlation between real wages and labor input as well as their relative variabilities in the following discussion.²² Because the working hours series published by the U.S. Bureau of Labor Statistics (BLS) has been widely used in the macroeconomic literature and the BLS hourly wage series has been widely used when researchers address the cyclicity of real wages,²³ the correlations between these two series are reported in Panel A of Table 1. Panel B reports the correlation between *AHW* (aggregate hourly wages) and aggregate hours worked (called *HRS* hereafter) of all nonselfemployed workers in the two CPS samples.²⁴ Data in rows (a)

²⁰For detailed discussion, please refer to the Appendix.

²¹To test the sensitivity of the results to the restriction of common β_s , I also estimate the cyclicity of real wages allowing β_s to vary over time. To allow for varying β_s but still identify *EUP*, I restrict the β_s to be the same across adjacent periods only. The results indicate that while the β_s vary significantly over time, the cyclical pattern of *EUP* are robust to this extension.

²²To make my results comparable with the predicted values from previous theoretical business models, I first logged all variables and then detrended them using the Hodrick-Prescott filter. In the annual data, following Backus and Kehoe (1992), the smoothing parameter in the H-P filter is set at 100. In the quarterly data, it is set at 1600.

²³The series published by the BLS are based on establishment survey. The hourly wage series covers private production workers.

²⁴In the quarterly data, the raw data shows a clear seasonal pattern, specifically total number of employment, labor quality and hourly wages always drop in the third quarter. The same phenomena have also been found in Hansen (1993). To attack this problem, I first deseasonalize all the data by the X11ARIMA method, the cyclical properties of the deseasonalized series are then studied. The X11ARIMA method is

Table 1: Correlation of labor input with its price

		<i>EUP</i>		<i>AHW</i>	
		Annual	Quarterly	Annual	Quarterly
		(1)	(2)	(3)	(4)
A: BLS data					
(a)	Aggregate HRS	.	.	0.3882 (0.1099)	0.1691 (0.1394)
B: MCPS annual data and ORG quarterly data					
(b)	Aggregate HRS	.	.	0.6593 (0.0803)	0.2999 (0.0889)
(c)	Aggregate EUS	0.8344 (0.0534)	0.2786 (0.1138)	.	.
C: ORG annual and quarterly data					
(d)	Aggregate HRS	.	.	0.7871 (0.0352)	0.2999 (0.0889)
(e)	Aggregate EUS	0.8071 (0.0430)	0.2786 (0.1138)	.	.

Notes: *AHW* and *HRS* series only covers production workers in private nonagricultural sector.
 Annual *BLS* data and *MCPS* data cover the 1975-1994 period.
ORG data and Quarterly *BLS* data cover the 1979-1993 period.
 Numbers in parenthesis are standard errors.

All variables are first logged and then detrended by the H-P filter.

and (b) of Table 1 show that the BLS wages are less procyclical than the CPS wages in the annual data. Presumably, the difference could result from only production workers being included in the BLS wage series. Because the employment of production workers fluctuates more than that of nonproduction workers over business cycles, changes in the labor quality should have a larger effect on the cyclical behavior of real wages. The most surprising finding in Table 1 is that real wages are strongly procyclical in the annual data, but only weakly procyclical in the quarterly data. Controlling for changes in labor quality increases the correlation between labor input and its price from 0.6593 between *AHW* and *HRS* to 0.8344 between *EUP* and *EUS* in the MCPS data. In the quarterly data (ORG), even though the correlation between *EUS* and *EUP* is 80 percent larger than that between *AHW* and *HRS*, it is only equal to 0.2786.

To test whether the discrepancy between annual and quarterly results arises from the use of different data sets, I compute both quarterly and annual data from ORG. The results are reported in Panel C of Table 1. Interestingly, the correlations between *EUS* and *EUP* obtained from the MCPS and annualized ORG data are almost identical. This implies that the disparity between annual and quarterly results is robust to the data choice.

Because correlations between the key variables and *GNP* are calibrated in many business cyclical models, I report those correlations in Table 2. The correlation between *EUP* and *GNP* is about three times larger in the annual than in the quarterly data. This further confirms that the cyclical behavior of real wages is sensitive to the frequency of data used. Data in columns (1) and (2) of Table 2 indicate that all the variables are more volatile in the annual data sets than in the quarterly ones. However, the relative variability between *HRS* and *AHW* in the quarterly (ORG) is higher than that in the annual data (MCPS). Controlling for labor quality also decreases the percentage standard deviations of labor input

also used by the U.S. Bureau of Labor Statistics. The raw data and the deseasonalized series are plotted in figure 1.

Table 2: Cyclical behavior of the U.S. economy.

	Volatility		Cross-correlation of real GNP with	
	Annual 75-94 (1)	Quarterly 79:01-93:04 (2)	Annual 75-94 (3)	Quarterly 79:01-93:04 (4)
A: BLS data				
HRS	2.41	1.62	0.9693 (0.0058)	0.9476 (0.0163)
AHW	1.56	0.85	0.6201 (0.0769)	0.3200 (0.1286)
B: MCPS annual data and ORG quarterly data				
HRS	1.90	1.63	0.9666 (0.0138)	0.8201 (0.0738)
AHW	1.78	1.27	0.6033 (0.0491)	0.1669 (0.1340)
EUS	1.74	1.63	0.9633 (0.0152)	0.7753 (0.0908)
EUP	1.72	1.14	0.8042 (0.0342)	0.2043 (0.1437)

Notes: Numbers in parentheses are standard errors. All variables are first logged and then detrended by the H-P filter. Volatility is measured by the standard deviation of the logged variable.

from 1.90 when it is measured by hours worked to 1.74 when it is measured by *EUS* in the annual data, but it does not significantly change its correlation with *GNP*. In the quarterly data (*ORG*), the volatility of *EUS* is the same as that of the *HRS*.

Given the fact that the cyclical behavior of the quality adjusted series differs from that of the unadjusted ones, it is informative to examine the cyclical behavior of labor quality directly. Under this rationale, I introduce two labor quality measures.

$$LQ = \frac{\sum_i \exp(\hat{\beta}_0 + X_{it}\hat{\beta}_1) h_{it}}{\sum_i h_{it}} = \frac{E_{it}}{\sum_i h_{it}}$$

and

$$MLQ = \exp\left[\frac{1}{N_t} \sum_i (\hat{\beta}_0 + X_{it}\hat{\beta}_1)\right]$$

LQ measures the hourly weighted average of efficiency labor units in period t , its fluctuations are influenced both by workers' moving in and out of the work force and changes in the correlation between X and h . MLQ ²⁵ measures the unweighted average of efficiency labor units in period t . Its fluctuations are only affected by workers' moving in and out of the work force. Differences in the cyclical behaviors of *MLQ* and *LQ* reveal whether the adjustment in the labor quality is mainly on the intensive margin or on the extensive margin.

Table 3 reports the cyclical properties of the *LQ* and *MLQ* series. A negative correlation between *MLQ* (*LQ*) and *GNP* in both the annual and quarterly data sets means that a countercyclical bias is induced by cyclical fluctuations in labor quality. On the one hand, the correlation between *LQ* and *GNP* is only 27 percent larger than that between *MLQ* and *GNP* in the annual data, implying that the adjustment in labor quality is mainly through adjusting the number of employed workers instead of their working hours. On the other

²⁵The cyclical behavior of the arithmetic mean of the labor quality, $\frac{1}{N_t} \sum \exp(\hat{\beta}_0 + X_{it}\hat{\beta}_1)$, is also examined. Its cyclical behavior is very similar to $\exp\left[\frac{1}{N_t} \sum_i (\hat{\beta}_0 + X_{it}\hat{\beta}_1)\right]$. Because $\exp\left[\frac{1}{N_t} \sum_i (\hat{\beta}_0 + X_{it}\hat{\beta}_1)\right]$ is a unbiased estimate of $\ln \lambda$, but $\frac{1}{N_t} \sum \exp(\hat{\beta}_0 + X_{it}\hat{\beta}_1)$ is only a consistent estimate of $\ln \lambda$, only the cyclicity of *MLQ* is reported later.

Table 3: Cyclical behavior of the U.S. economy.

	Volatility		Cross-correlation of real GNP with	
	Annual 75-94	Quarterly 79:01-93:04	Annual 75-94	Quarterly 79:01-93:04
MLQ	0.26	0.18	-0.5331 (0.1014)	-0.0058 (0.1127)
LQ	0.24	0.22	-0.6757 (0.0553)	-0.3287 (0.1272)

Notes: Numbers in parentheses are standard errors. All variables are first logged and then detrended by the H-P filter. Volatility is measured by the standard deviation of the logged variable.

hand, an acyclical *MLQ* and a countercyclical *LQ* at the quarterly data indicate that the adjustment of the labor force is mainly through working hours of employed workers, *i.e.* in the extensive margin.

In Figures 2 and 3, I plot the cyclical components of the key variables. In the annual data, the *EUS* series lies inside the *HRS* series, implying that the quality adjusted labor input series is less variable. A joint reading of Figures 2b and 2d shows that labor quality always reaches its minimum value when *GNP* begins to decrease, and *MLQ* (*LQ*) usually reaches its minimum value when *GNP* reaches its maximum value and *vice versa*, implying that the low skilled workers' share of working hours increases as the economy moves from troughs to booms. In the quarterly data, there are no significant differences between the quality adjusted and unadjusted series.

In summary, the above results indicate that changes in labor quality mitigate the fluctuations of aggregate real wages and its correlation with aggregate output in both annual and quarterly data. However, *EUP* is strong procyclical in the annual data and only weakly procyclical in the quarterly data, implying that the cyclicity of *EUP* heavily depends on the data frequency.

To gain more insight into this disparity, I further aggregate the monthly data at different frequencies, added a month at a time. Then the correlations between *EUP* (*AHW*) and

EUS (HRS) are estimated²⁶ at each frequency. Figure 4a(4b) shows that the correlation between *EUP (AHW)* and *EUS (HRS)* increases almost monotonically as the frequency of the data becomes lower, with a small dip at the semi-annual point. Even this small dip disappears when I pool February to July and August to January together instead of January to June and July to December.²⁷ This experiment further confirms that the cyclical-ity of real wages are sensitive to the data frequency, and raises interesting questions for business cycle models.

To examine whether the aggregate wage series also follows the same pattern, Figures 5a and 5c plot the relationship between the cyclical-ity of the BLS hourly wages and the frequency of data used. It turns out that the correlation between *AHW* and *HRS* reaches its maximum value at the quarterly level in the aggregate data, implying that the cyclical-ity of aggregate hourly wages is not sensitive to whether quarterly or annual data is used for the 1964-1975 period. This can explain why the strong relationship between the cyclical-ity of real wages and the data frequency used has never been documented. However, as shown in 5b, the negative relationship between the cyclical-ity of real wages and the data frequency holds in the 1975-1994 period if all production workers in the nonagricultural private sector are included. This implies that the cyclical-ity of real wages might have changed in the past two decades.

²⁶Because the cyclical behavior of the time series could be distorted by the X11 adjustment, following Barsky and Miron (1989), I first use H-P filter to remove the long run trend, and then remove the deterministic seasonal patterns based on the following equation

$$x_t = \sum_{i=1}^I \varphi d_t^s + \zeta_t$$

where x_t is the detrended series and ζ_t is the stochastic component of x_t and d_t^s are the seasonal dummies.

²⁷The results are plotted in Figure 4c and 4d.

4.2 Sensitivity Analysis

4.2.1 Sample Period

Given the fact that the cyclical behavior of real wages in the aggregate data is sensitive to the sample period, it is natural to ask whether the cyclical behavior of the price of efficiency labor units also depends on the sample period. There are at least two sources that could change the cyclical behavior of *EUP*. First, labor market deregulation may have changed the cyclical behavior of labor quality. Second, different shocks have different implications on labor productivity and the intensities of these shocks may have varied over time. Because most panel data sets only cover a relatively short period, the sensitivity of the cyclical behavior of real wages to the sample period has never been examined in previous panel studies. The relatively longer period covered by the MCPS data provides an opportunity to address this issue.

Since the number of weeks worked is recorded in brackets and the usual weekly working hours are not available for the 1963-1974 period, if one wants to use the early period data of the MCPS, some imputations have to be made. I use the mean of weeks worked for the corresponding category in 1975 as the proxy of weeks worked before 1975. I use the last week's working hours as a proxy of usual weekly working hours for those who worked in both the last week and the last year, and use the cell means of the post-1975 period for those who did not work in the last week but worked in the last year.²⁸

Columns (1) and (2) of Tables 4²⁹ and 5 report the cyclical behavior of the key variables when the longer period data is used and columns (3) and (4) reproduce the results from Tables 1, 2 and 3, respectively. Data in Table 4 show that all the correlations decrease and all volatilities increase when the data in the earlier period are included. For example, the correlation with real *GNP* decreases by 20 and 21 percent for *AHW* and *EUP*, respectively. The volatility

²⁸See the Appendix for detailed discussion.

²⁹Usual weekly working hours are used for the 1975-1994 period in computing the annual working hours. and the imputed working hours and imputed working weeks are used for the 1963-1974 period.

Table 4: Cyclical behavior of the U.S. economy

	Volatility		Cross-correlation of real GNP with	
	63-94	75-94	63-94	75-94
	(1)	(2)	(3)	(4)
Aggregate EUS	1.86	1.74	0.8851 (0.0388)	0.9633 (0.0152)
Aggregate HRS	1.99	1.90	0.9049 (0.0370)	0.9666 (0.0138)
MLQ	0.26	0.26	-0.4855 (0.0909)	-0.5331 (0.1014)
LQ	0.27	0.24	-0.5475 (0.1044)	-0.6757 (0.0553)
EUP	1.75	1.72	0.6288 (0.0918)	0.8042 (0.0342)
AHW	2.02	1.78	0.4787 (0.1060)	0.6033 (0.0491)

Notes: Imputed weekly hours are used for the 1963-1974 period. Numbers in parentheses are standard errors. All variables are first logged and then detrended by the H-P filter. Volatility is measured by the standard deviation of the logged variable.

Table 5: Correlation of labor input with its price.

	<i>EUP</i>		<i>AHW</i>	
	63-94	75-94	63-94	75-94
	(1)	(2)	(3)	(4)
Aggregate EUS	0.5980 (0.1444)	0.8344 (0.0534)	.	.
Aggregate HRS	.	.	0.5041 (0.1198)	0.6593 (0.0695)

Notes: Imputed weekly hours are used for the 1963-1974 period. Numbers in parentheses are standard errors. All variables are first logged and then detrended by the H-P filter.

of *AHW* increases by 13 percent. Therefore the lower procyclicality of real wages in the 1963 – 1974 period is not a result of less variability in real wages over that period. To gain further insight on this issue, I plot the cyclical components of the key variables in Figure 7. Even though including the early period data reduces all the correlations, it is difficult if not impossible to discern any systematic changes over the 1963-1994 period. The irregular changes in *AHW*, *EUP* and *MLQ* during the 1970-1974 period are likely to account for most of the decrease.³⁰

The results of this subsection show that the duration of the business cycles could be a factor that influences the cyclicity of aggregate real wages. When the sample period is dominated by several relatively short lived cycles, real wages and employment are likely to be on their adjustment paths most of the time, as in the 1970-1974 period, so the correlation between employment and real wages tends to be small, and their volatility large. This also helps to explain why results based on the NLS and on the PSID differ from each other. The sample period covered by the NLS is the 1966-1980 period which is dominated by two short-lived cycles (1970-1974, 1975-1980). As one can see from Figure 7, labor quality moves irregularly during the 1970-1974 period, so it is not surprising that Bils (1985), using the NLS data, finds that changes in the composition of the labor force are relatively unimportant. However, once a longer period of data is used, that includes longer cycles, such as Solon *et al.* (1994),³¹ fluctuations in labor quality follow a more regular pattern and changes in labor quality play a more important role.

4.2.2 Sample Composition

The strong countercyclicality of labor quality found here markedly differs from Blank (1990a), where she finds that changes in the characteristics of workers are acyclical. Presumably, the

³⁰After excluding these five years, the correlations in tables 4 and 5 increase.

³¹The PSID data for the 1968-1988 period were used in Solon *et al.* (1994).

Table 6: Cyclical behavior of the components of human capital.

Variable	Cyclicity				
	Household heads				
	(1)	Black	White	Black	White
	75-94	69-82	69-82	69-82	69-82
Education	-0.0083 (0.0034)	0.0110 (0.0100)	0.0010 (0.0039)	-0.0157 (0.0133)	-0.0001 (0.0023)
Experience	-0.0165 (0.0164)	-0.0837 (0.0432)	-0.0196 (0.0154)	.	.
South	-0.0007 (0.0004)	0.0006 (0.0015)	-0.0006 (0.0004)	.	.
Part-time	-0.0015 (0.0003)	-0.0004 (0.0010)	-0.0008 (0.0002)	.	.
Sex	-0.0003 (0.0003)
Age	.	.	.	0.0402 (0.0615)	0.0052 (0.0250)

Note: Numbers in parentheses are standard errors.

source of the disparity could be that only prime age male household heads³² are included in her study. Since individuals in this group generally have a stronger labor market attachment than others, there would be few workers who are out of employment for an entire year. To test this hypothesis, I estimate the cyclicity of the means of the variables which compose the X vector in the hedonic function by running the following regression:

$$X_t - X_{t-1} = \alpha_0 + \alpha_1 [(GNP_t - GNP_{t-1}) / GNP_{t-1}] + \epsilon_t \quad (5)$$

The estimation results are reported in column (1) of Table 6. The mean level of education is strongly countercyclical, implying that less educated workers are the first to be laid off in recessions. A strong countercyclical part-time dummy shows that there are more workers switching from full-time to part-time jobs in recessions.

To investigate the sources of the discrepancy between the results found here and Blank (1990a), I re-estimate equation (5) for the 1969-1982 period (the period covered by Blank's

³²Her sample only consists of male household heads of age 20 to 65 in 1969-1982.

study), and restrict the sample to male household heads with an age of 20 to 65. Following Blank (1990a), I estimate equation (5) for white and black workers separately. The estimation results are reported in columns (2) and (3) of Table 5. For comparison purpose, Blank's results (p26, Table 2) are reproduced in columns (4) and (5). Consistent with Blank (1990a), the mean levels of education are acyclical for both white and black workers. The average years of experience is also acyclical for white male workers. To the extent that years of education and experience are good measures of labor skill, this finding supports the view that fluctuations in real wages are not seriously biased by workers moving in and out of the work force over the business cycle for white male household heads. However, the average years of experience of black workers are countercyclical, implying that less experienced black workers are likely to be laid off in economic downturns. A comparison between columns (2) and (4) as well as (3) and (5) of Table 6 indicates that the differences between Blank's results and the ones found here are statistically insignificant. Therefore, if one is only interested in fluctuations in real wages of prime age males, changes in labor quality are not a big concern. However, if one is interested in the cyclical behavior of real wages for the entire economy, changes in labor quality have to be considered.

Another issue regarding sample composition is that while most of the macroeconomic literature has focused on private, nonagricultural sectors, the earnings data of the entire economy has been used in previous micro studies. To examine whether excluding public and agricultural workers changes the picture, I re-estimate the cyclical behavior of the key variables for private, nonagricultural workers. The estimation results are reported in columns (1), (3), (5) and (7) of Tables 7 and 8, and the results based on the larger sample are reproduced in columns (2), (4), (6) and (8). Data in Tables 7 and 8 indicate that there are only minor differences in the cyclical behaviors of most variables in the two samples.

In the annual data, the two labor quality measures in the second sample are somewhat more volatile than in the first one, and they are more closely correlated with real *GNP*,

Table 7: Cyclical behavior of the U.S. economy: private, nonselfemployed nonagricultural workers.

	Volatility				Cross-correlation of real GNP with			
	Annual		Quarterly		Annual		Quarterly	
	75-94		79:01-93:04		75-94		79:01-93:04	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Aggregate EUS	1.31	1.74	1.73	1.63	0.9014 (0.0245)	0.9633 (0.0152)	0.8181 (0.0775)	0.7753 (0.0908)
Aggregate HRS	1.97	1.90	1.76	1.63	0.9479 (0.0203)	0.9666 (0.0138)	0.8570 (0.0591)	0.8201 (0.0738)
AHW	1.77	1.78	0.93	1.27	0.6122 (0.0470)	0.6033 (0.0491)	0.0765 (0.1144)	0.1669 (0.1340)
EUP	1.74	1.72	0.77	1.14	0.8218 (0.0338)	0.8042 (0.0342)	0.1661 (0.1357)	0.2043 (0.1437)
MLQ	0.30	0.26	0.20	0.18	-0.5899 (0.0773)	-0.5331 (0.1041)	-0.0622 (0.1236)	-0.0058 (0.1127)
LQ	0.79	0.24	0.17	0.22	-0.8790 (0.0348)	-0.6757 (0.0553)	-0.0961 (0.0972)	-0.3287 (0.1272)

Notes: Numbers in parentheses are standard errors. All variables are first logged and then detrended by the H-P filter. Volatility is measured by the standard deviation of the logged variable.

Table 8: Correlation of labor input with its price: private, nonselfemployed, nonagricultural workers.

	<i>EUP</i>				<i>AHW</i>			
	Annual		Quarterly		Annual		Quarterly	
	75-94		79:01-93:04		75-94		79:01-93:04	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Aggregate EUS	0.7492 (0.0619)	0.8344 (0.0534)	0.2533 (0.1182)	0.2786 (0.1138)
Aggregate HRS	0.7263 (0.0465)	0.6593 (0.0803)	0.2104 (0.0807)	0.2999 (0.0889)

Notes: Numbers in parentheses are standard errors. All variables are first logged and then detrended by the H-P filter.

implying that the employment of low skilled workers in the private sector is more sensitive to the economic condition. This implies that business cycles have different impact on the employment of public and private sector. Another difference is that AHW in the private sector are less procyclical than that in the entire economy in the quarterly data. However, those differences have no significant effect on the cyclicity of EUP , indicating that the cyclicity of EUP is not sensitive to whether public and agricultural workers are included or not.

4.2.3 Sample Selection Bias

In previous sections the conditional distribution of the error term ($\varepsilon|w > 0$) is assumed to be constant. If workers with lower levels of unobserved skill ε are more likely to be laid off in recessions, $\bar{X}\hat{\beta}$ underestimates the mean level of the labor quality, and $EUP(\overline{\ln w} - \bar{X}\hat{\beta})$ overestimates the price of labor input in recessions. Therefore the results presented earlier could overstate the procyclicity of real wages. To address this issue, Heckman's two-stage estimation method is applied.³³ Because workers' participation decisions are dependent on economic conditions, the coefficient on the selection term varies over time. Obviously, fixing all the β 's in the base year level is not appropriate in this case. To handle this problem, I assume there are no dramatic changes of the coefficients of the participation equation in adjacent periods. Even though this assumption is strong, a comparison between the results from the section 4.1 and the ones in which the selection bias is partially corrected can still reveal whether the selection bias is a serious problem. The cyclicity of the key variables are reported in columns (1), (3), (5) and (7) of Tables 9 and 10 and data in Tables 1, 2 and 3 are reproduced in columns (2), (4), (6) and (7). The results are very close to the results

³³In the first stage, a probit model is estimated. The explanatory variables in the annual data are years of education, years experience, experience squared, sex dummy, south dummy, marital status dummy, a race dummy and the number of children under six. The number of children under six is not included in the quarterly data due to the limitation of the data. In the second stage, the inverse of the estimated Mill's ratio is included in the wage equation. The pseudo R^2 in the first stage estimation is around 0.10.

Table 9: Cyclical behavior of the U.S. economy

	Volatility				Cross-correlation of real GNP with			
	Annual		Quarterly		Annual		Quarterly	
	75-94		79:01-93:04		75-94		79:01-93:04	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Aggregate EUS	1.36	1.74	1.30	1.63	0.9622	0.9633	0.8412	0.7753
					(0.0144)	(0.0152)	(0.0639)	(0.0908)
Aggregate HRS	1.90	1.90	1.63	1.63	0.9666	0.9666	0.8201	0.8201
					(0.0138)	(0.0138)	(0.0738)	(0.0738)
AHW	1.78	1.78	0.87	1.27	0.6033	0.6033	0.1669	0.1669
					(0.0491)	(0.0491)	(0.1340)	(0.1340)
EUP	1.73	1.72	0.90	1.14	0.8032	0.8042	-0.0280	0.2043
					(0.0339)	(0.0342)	(0.1523)	(0.1437)
MLQ	0.27	0.26	0.17	0.18	-0.4835	-0.5331	0.0269	-0.0058
					(0.1420)	(0.1041)	(0.1028)	(0.1127)
LQ	0.56	0.24	0.39	0.22	-0.9443	-0.6757	-0.6180	-0.3287
					(0.0202)	(0.0553)	(0.1014)	(0.1272)

Notes: Numbers in parentheses are standard errors. All variables are first logged and then detrended by the H-P filter. Volatility is measured by the standard deviation of the logged variable.

based on the simple *OLS* regression, implying that the sample selection bias has no major effect on the cyclicity of the key variables.

5 Conclusion

In this paper, I developed and implemented a hedonic pricing method for examining the true cyclicity of real wages. The flexibility of the hedonic method has made it possible to replicate and reconcile the results of a number of the major cyclicity studies on a single data set, to arrive at a clear interpretation of the currently available evidence. The results indicate that there is a strong relationship between the cyclicity of real wages and the data frequency. Namely, real wages are strongly procyclical in the annual data but are weakly procyclical in the quarterly data. The strong procyclicity appears after aggregating the data over 5 months or longer. Even though the strong procyclicity of real wages in the

Table 10: Correlation of labor input with its price, 1975-1994

	<i>EUP</i>				<i>AHW</i>			
	Annual		Quarterly		Annual		Quarterly	
	75-94		79:01-93:04		75-94		79:01-93:04	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Aggregate EUS	0.7947 (0.0645)	0.8344 (0.0534)	-0.0767 (0.1248)	0.2786 (0.1138)
Aggregate HRS	0.6593 (0.0803)	0.6593 (0.0803)	0.2999 (0.0889)	0.2999 (0.0889)

Notes: Selection bias is corrected. Numbers in parentheses are standard errors.

All variables are first logged and then detrended by the H-P filter.

annual data is consistent with RBC models, the weakly procyclicality of real wages in the quarterly data seems to favor models that posit the existence of a countercyclical markup. Unfortunately, none of the current business cycle models can explain the variation in real wage cyclicity in the quarterly and annual data. The significant difference in the cyclicity of quarterly and annual data and its robustness to different data and model specifications suggests that further research focusing on this finding in the context of competing business cycle models would be especially fruitful.

Appendix: A Proof of Consistency

Because unobserved skills may correlate with personal characteristics, the *OLS* estimates of the β s may be inconsistent. Even in this case, one can show that *EUP* is still a consistent estimate of the price of the labor input.

By definition, the efficiency units of labor embodied in worker i is:

$$\ln l_i = \beta_0 + \beta_1 X_i + \eta_i + \epsilon_i \quad (\text{A.1})$$

where X_i are the personal characteristics of worker i , β_0 is a constant, $\eta_i \sim (0, \sigma_\eta^2)$ represents some personal characteristics which are not directly observable to the econometrician and are correlated with X_i , and $\epsilon_i \sim (0, \sigma_\epsilon^2)$ is the error term which is observable to the firm but not to the econometrician and uncorrelated with X_i . Suppose that workers are paid by:

$$w_i^* = \lambda l_i = \lambda \exp(\beta_0 + \beta_1 X_i + \eta_i + \epsilon_i) \quad (\text{A.2})$$

However, one can only observe

$$w_i = w_i^* * v_i$$

where v_i is a measurement error and is assumed to follow *iid* $N(0, \sigma_v^2)$. Fluctuations in λ and $\overline{\ln l}$ are what we are interested in. Because l_i cannot be observed directly, it has to be estimated using equation (4). Due to the correlation between X_i and η_i , $\ln \hat{l}_i$ may be a poor estimator of $\ln l_i$.

However, if

$$\text{cov}(X_i, \eta_i) = \sigma_{x\eta}$$

and,

$$\gamma = \frac{\sigma_{x\eta}}{\sigma_X \sigma_\eta}$$

then

$$p \lim \hat{\beta}_1 = \beta + \frac{\gamma \sigma_{x\eta}}{\sigma_X^2}.$$

Therefore,

$$\begin{aligned} p \lim \hat{\beta}_0 &= p \lim (\ln l) - p \lim \hat{\beta}_1 \times p \lim \bar{X} \\ &= \beta_0 + \beta_1 \mu_X - \left(\beta_1 + \frac{\gamma \sigma_{x\eta}}{\sigma_X^2} \right) \mu_X \\ &= \beta_0 - \frac{\gamma \sigma_{x\eta}}{\sigma_X^2} \mu_X \end{aligned}$$

$$\begin{aligned} p \lim (\hat{\beta}_0 + \hat{\beta}_1 X) &= p \lim \hat{\beta}_0 + p \lim \hat{\beta}_1 \times \mu_X \\ &= \beta_0 - \frac{\gamma \sigma_{x\eta}}{\sigma_X^2} \mu_X + \beta_1 \mu_X \\ &= \beta_0 + \beta_1 \mu_X \end{aligned}$$

where $\mu_X = E(X)$, σ_X^2 is the variance of X and $\hat{\beta}_0$ and $\hat{\beta}_1$ are the OLS estimator from equation (4). So, $\frac{1}{N_t} \sum_{i=1}^{i=N_t} \ln \widehat{l}_{i,t}$ is a consistent estimator of $\overline{\ln l_t}$ and

$$\frac{1}{N_t} \left(\sum_i^{i=N_t} \ln w_{it} - \sum_i^{i=N_t} \ln \widehat{l}_{it} \right)$$

is a consistent estimator of $\ln \lambda$ if $\sum \ln v_i = 0$, where N_t is the total number of employment in period t .

Appendix: B Estimating the Labor Income for Top Coded Observations

The real log annual income, y_{it}^* is assumed to follow:

$$y_{it}^* = \alpha_{0t} + \alpha_{1t} Edu_{it} + \alpha_{2t} Exp_{it} + \alpha_{3t} ExpS_{it} + \alpha_{4t} S_{it} + \alpha_{5t} PT_{it} + \alpha_{6t} South_{it} + \alpha_{7t} WK_{it} + \epsilon_{it}$$

where WK_{it} is weeks worked by individual i in year t , and all the other variables have the same meanings as in section 3. Because the labor incomes are top coded for some individuals, what we observe is

$$y_{it}^* = \alpha_{0t} + \alpha_{1t} Edu_{it} + \alpha_{2t} Exp_{it} + \alpha_{3t} ExpS_{it} + \alpha_{4t} S_{it} + \alpha_{5t} PT_{it} + \alpha_{6t} South_{it} + \alpha_{7t} WK_{it} + \epsilon_{it}$$

Table B.1: Values used in imputing top coded labor income

year	value	year	value	year	value	year	value	year	value	year	value
1963	1.00	1969	1.31	1975	1.32	1981	1.40	1987	1.46	1993	1.25
1964	1.00	1970	1.30	1976	1.35	1982	1.46	1988	1.00	1994	1.30
1965	1.00	1971	1.32	1977	1.34	1983	1.51	1989	1.00		
1966	1.00	1972	1.31	1978	1.38	1984	1.00	1990	1.00		
1967	1.33	1973	1.34	1979	1.48	1985	1.42	1991	1.00		
1968	1.33	1974	1.37	1980	1.49	1986	1.43	1992	1.00		

Note: 1.00 means that there are no labor income top coded in that year. For the period before 1977, values used here are very close to 1.33 (Juhn, Murphy and Pierce (1993)) while the value used after 1977 are pretty close to 1.44 used in later studies.

if $y_{it}^* < y_{Tt}$, and

$$y_{it} = y_{Tt} \text{ if } y_{it}^* \geq y_{Tt}$$

where y_{Tt} is the top coded value in year t . By assuming $\varepsilon \sim N(0, \sigma^2)$, the α s can be estimated based on standard maximum likelihood estimation. Then

$$\bar{y}_t = \hat{\alpha}_{0t} + \hat{\alpha}_{1t} \overline{Edu}_{it} + \hat{\alpha}_{2t} \overline{Exp}_{it} + \hat{\alpha}_{3t} \overline{ExpS}_{it} + \hat{\alpha}_{4t} \overline{S}_{it} + \hat{\alpha}_{5t} \overline{PT}_{it} + \hat{\alpha}_{6t} \overline{South}_{it} + \hat{\alpha}_{7t} \overline{WK}_{it}.$$

is a consistent estimator of the population mean of y_t^* .

I impute annual labor income for top coded observation as a constant times the top coded value so that the sample mean of the log annual labor income matches \bar{y}_t . It should be noted that in the MCPS, even though some workers are coded as top coded, their actual annual labor incomes might be below the top coded value. Those observations are treated as not top coded in this paper. The series of constants being used are reported in table B.1

In the quarterly data, the real log hourly wage, y_{it}^* is assumed to follow:

$$y_{it}^* = \alpha_{0t} + \alpha_{1t} Edu_{it} + \alpha_{2t} Exp_{it} + \alpha_{3t} ExpS_{it} + \alpha_{4t} S_{it} + \alpha_{5t} PT_{it} + \alpha_{6t} South_{it} + \epsilon_{it}$$

The series of constants is then constructed following the same procedure, and is reported in table B.2.

Table B.2: Values used in imputing top coded labor income

Time	value	Time	value	Time	value	Time	value	Time	value	Time	value
1979:1	1.183	1981:3	1.224	1984:1	1.279	1986:3	1.299	1989:1	1.228	1991:3	1.239
1979:2	1.209	1981:4	1.232	1984:2	1.283	1986:4	1.318	1989:2	1.236	1991:4	1.247
1979:3	1.192	1982:1	1.235	1984:3	1.290	1987:1	1.315	1989:3	1.234	1992:1	1.223
1979:4	1.204	1982:2	1.253	1984:4	1.288	1987:2	1.305	1989:4	1.242	1992:2	1.220
1980:1	1.200	1982:3	1.264	1985:1	1.298	1987:3	1.323	1990:1	1.250	1992:3	1.232
1980:2	1.208	1982:4	1.261	1985:2	1.310	1987:4	1.347	1990:2	1.233	1992:4	1.239
1980:3	1.199	1983:1	1.274	1985:3	1.294	1988:1	1.338	1990:3	1.255	1993:1	1.237
1980:4	1.219	1983:2	1.261	1985:4	1.302	1988:2	1.324	1990:4	1.246	1993:2	1.247
1981:1	1.230	1983:3	1.270	1986:1	1.303	1988:3	1.339	1991:1	1.228	1993:3	1.247
1981:2	1.221	1983:4	1.275	1986:2	1.303	1988:4	1.226	1991:2	1.224	1993:4	1.242

Appendix: C Definition of Variables

C.1 Working Hours and weeks

Before 1975, working weeks are recorded in 8 categories and usual weekly working hours are not available, some imputations have to be made if one wants to use the CPS data for the 1963-1974 period. For working weeks, I use the mean of weeks worked for the corresponding category in 1976. Two methods have been used to impute usual weekly working hours in previous studies. One is simply to use hours worked in the previous week as a proxy for the usual hours worked per week in the last year.³⁴ The other method is to use the cell means for the post-1976 data (Carrington, McCue and Pierce 1996), with cells defined according to some personal characteristics, such as education, experience *etc.* The shortcoming of the second approach is that both the cyclical and secular changes in weekly working hours have to be ignored. Figure 6 plots the actual usual weekly working hours as well as the imputed

³⁴This method is used in Angrist (1990) and Heckman and Sedlacek(1985). Even though the correlation between the last week's working hours and the usual weekly working hours is larger than 0.73, two problems may arise from using the last week's working hours as a proxy for usual hours worked per week in the last year. First, about 10% workers who reported positive labor income in the 1975 – 1994 period do not report their last week's working hours. Therefore, these workers have to be excluded in this approach. If the personal characteristics of these workers systematically differ from those of others, the estimation result would be biased by discarding these observations. Second, using the last week's working hours may introduce some biases in estimating annual working hours. The notion is that in the trough, the last week's working hours are likely to overestimate usual weekly working hours while the inverse happens in booms.

ones for the 1975-1994 period. It is clear that workers who have worked in both the previous week and the previous year have longer working hours than others. On the other hand, using cell means obviously underestimates the variability of working hours. In this study, for those who have worked in the last week, their working hours in the last week are used as a proxy for their usual weekly working hours in the last year; for those who did not work in the last week but have worked in the last year, I impute their weekly working hours based on the second approach. The cell is defined according to the following criteria: whether the worker has worked or not in the last week, male or female, age (16-20, 21-25, 26-30, 31-35, 36-40, 41-45, 46-50, 51-55, 56-60, 61-65, 66 and above), education (1-4, 5-9, 10-11, 12, 13-15, 16, 17 and above). To evaluate the consequences of the imputation, I apply all three methods to the 1975-1994 period. The cyclicalities of the key variables based on the third approach is the closest to the actual one.

C.2 Aggregate Hourly Wages

In the MCPS, aggregate hourly wages are defined as:

$$w_{at} = \frac{\sum INC_{it}}{\sum h_{it}}$$

where INC is workers' real annual wage and salary incomes, and h is annual working hours.

In the ORG, aggregate hourly wages are defined as:

$$w_{at} = \frac{\sum w_{it}h_{it}}{\sum h_{it}}$$

where w is the usual hourly wage of hourly workers, h is the last week's working hours.

To impute the hourly wages for those who worked for pay in the ORG but did not report a wage, I first estimate the equation (4) for each quarter using the observations for which wages are recorded. Hourly wages for those whose wages are not recorded are then predicted based on the estimation results.

C.3 Population

There are significant changes in the weighting scheme in the CPS in January 1982 due to the introduction of the 1980 census and in January 1986 due to the revision of population controls, the CPS weights have to be adjusted in order to keep the aggregate measure of labor input and labor incomes comparable over time. The adjustment made in 1982 caused substantial increases in the estimates of total population and persons in all labor force categories. According to *Employment and Earnings* (February 1982), 3000 labor force series were adjusted back to January 1970.³⁵ The 1986 revision also leads some series to be revised back to January 1980. To prevent changes in the aggregate labor input from being influenced by changes in the weighting scheme, I scaled the CPS weight so that the summation of the March Supplement Weight in the MCPS matches the March U.S. population in the corresponding year and the summation of the Earning Weight in the ORG matches the U.S. population in the corresponding month. The U.S. population reported in the Citibase databank is used as the benchmark for the adjustment.

³⁵Based on the CPS weight, the civilian non-institutional population increased by 4 percent in 1981, while the revised series show that it increased by only 1 percent.

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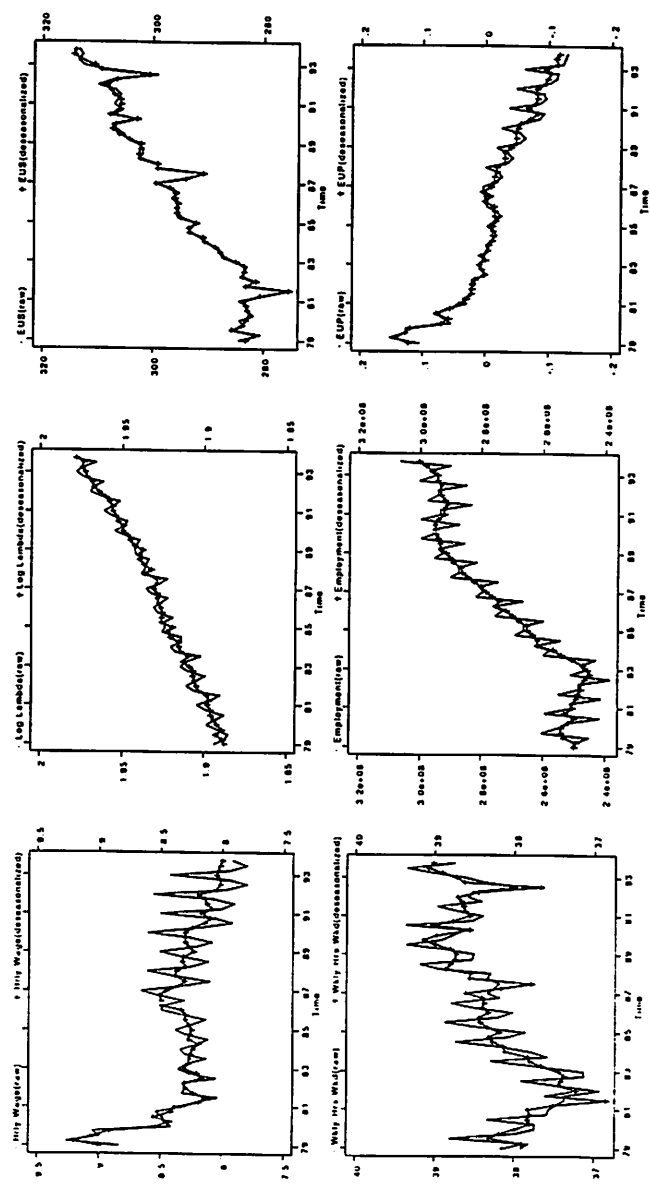
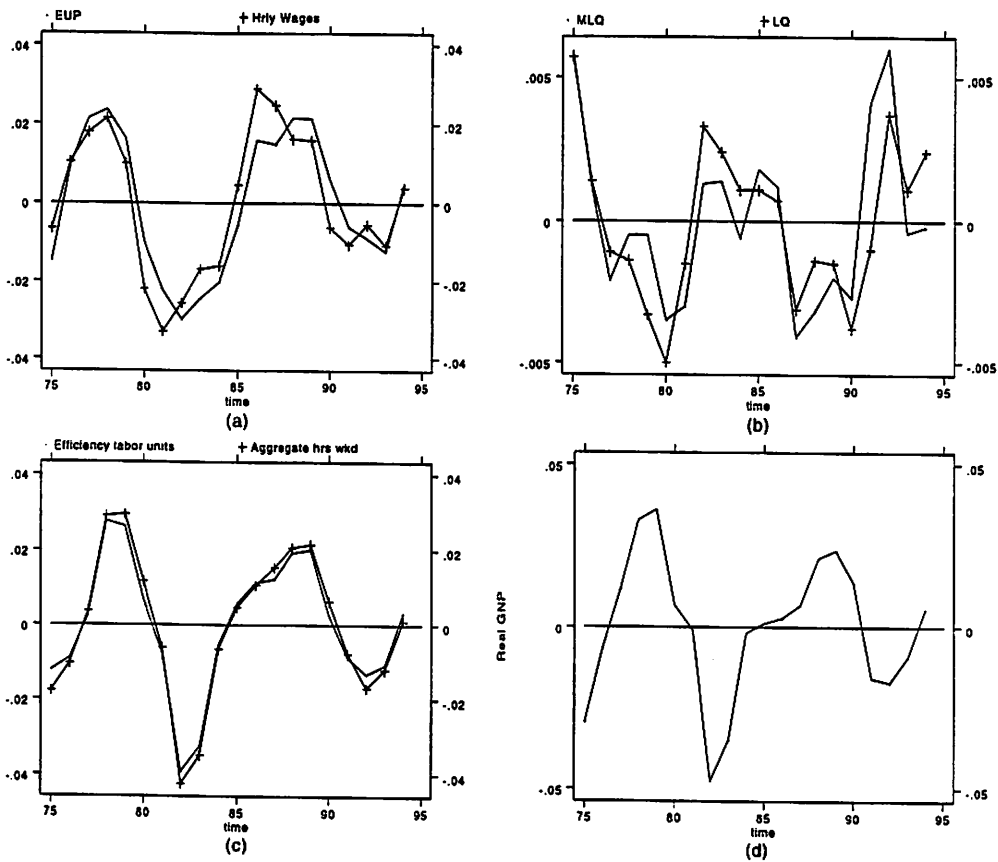


Figure 1: Raw and deseasonalized data in the quarterly data

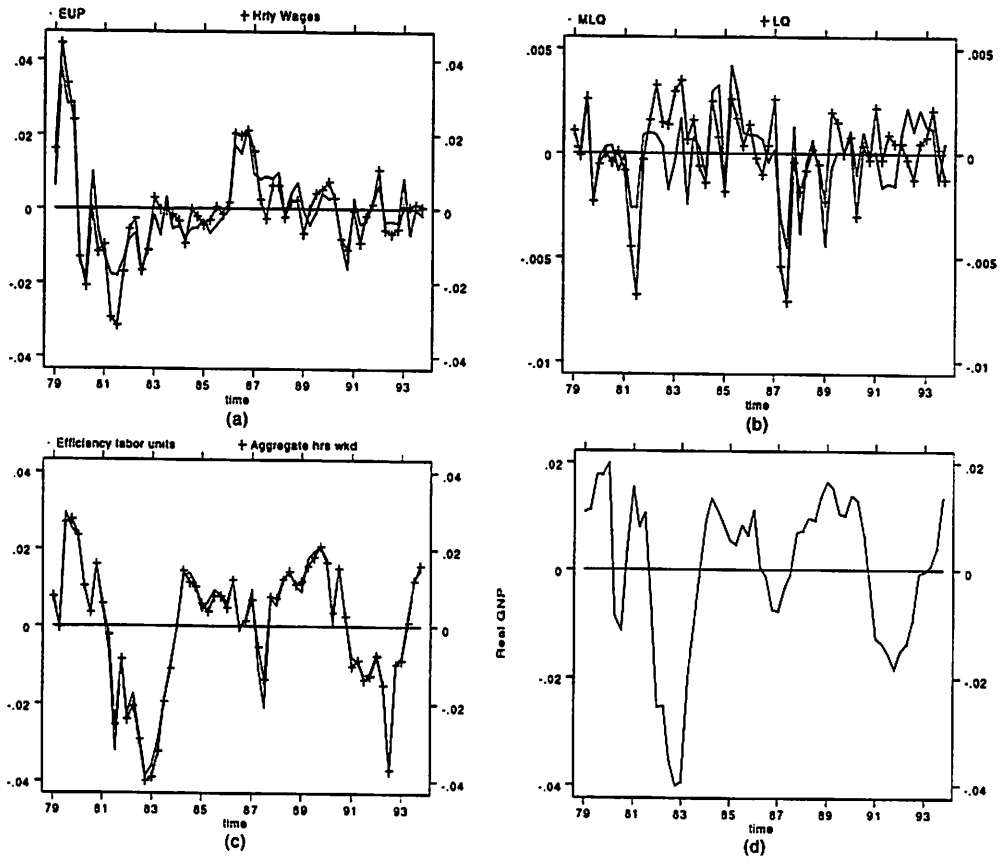
Non-self-employed workers, 1979:1-1993:4



Non-self-employed workers, 1975-1994

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Figure 2: Cyclical variations in the annual data



Non-self-employed workers, 1979:1-1993:4

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Figure 3: Cyclical variations in the quarterly data

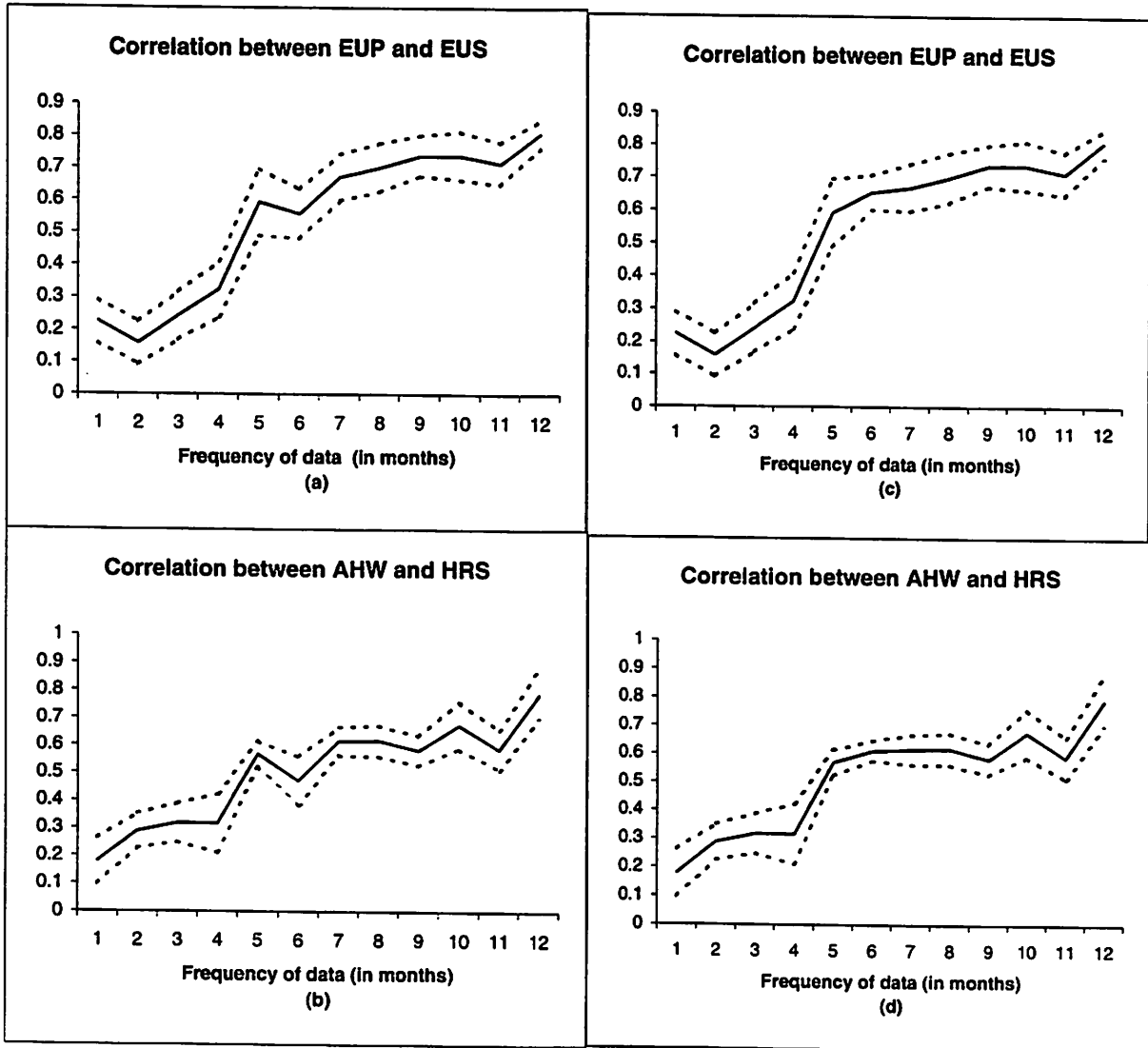
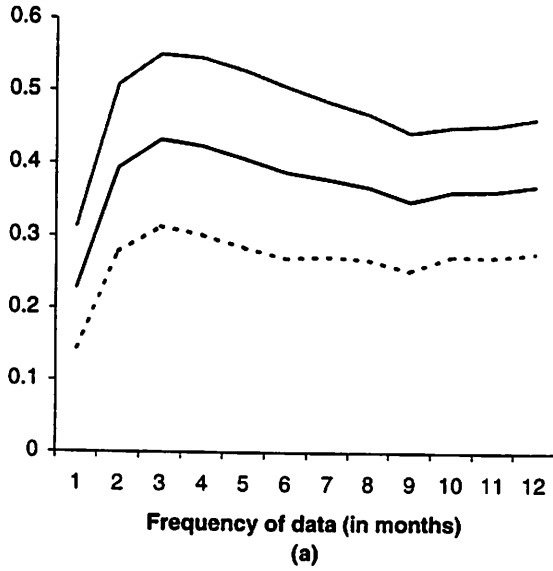
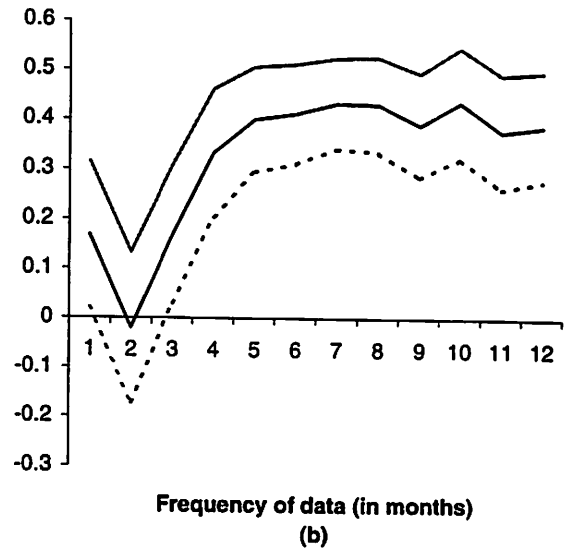


Figure 4: The correlation between labor input and its price, with \pm standard errors as upper and lower bounds indicated by dotted lines.

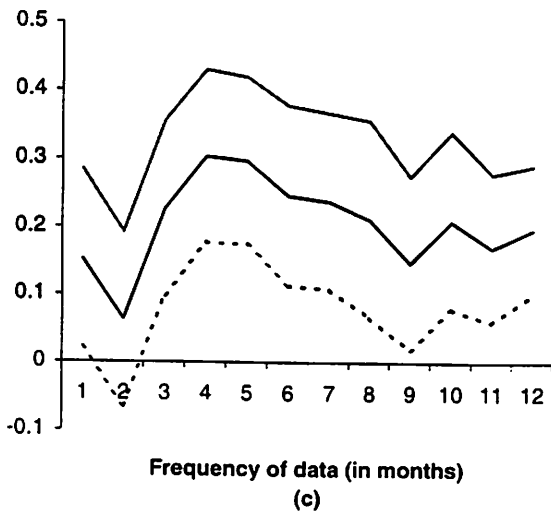
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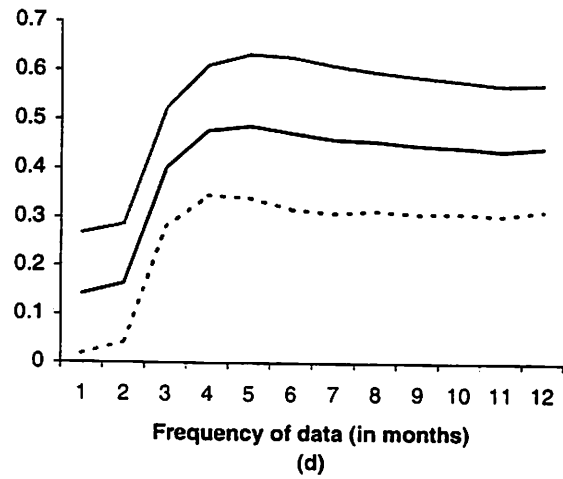
1975-1994, Production workers



1947-1994, Manufacturing Production workers



1975-1994, Manufacturing Production workers



Correlation between AHW and HRS

Figure 5: The correlation between labor input and its price, with \pm standard errors as upper and lower bounds indicated by dotted lines.

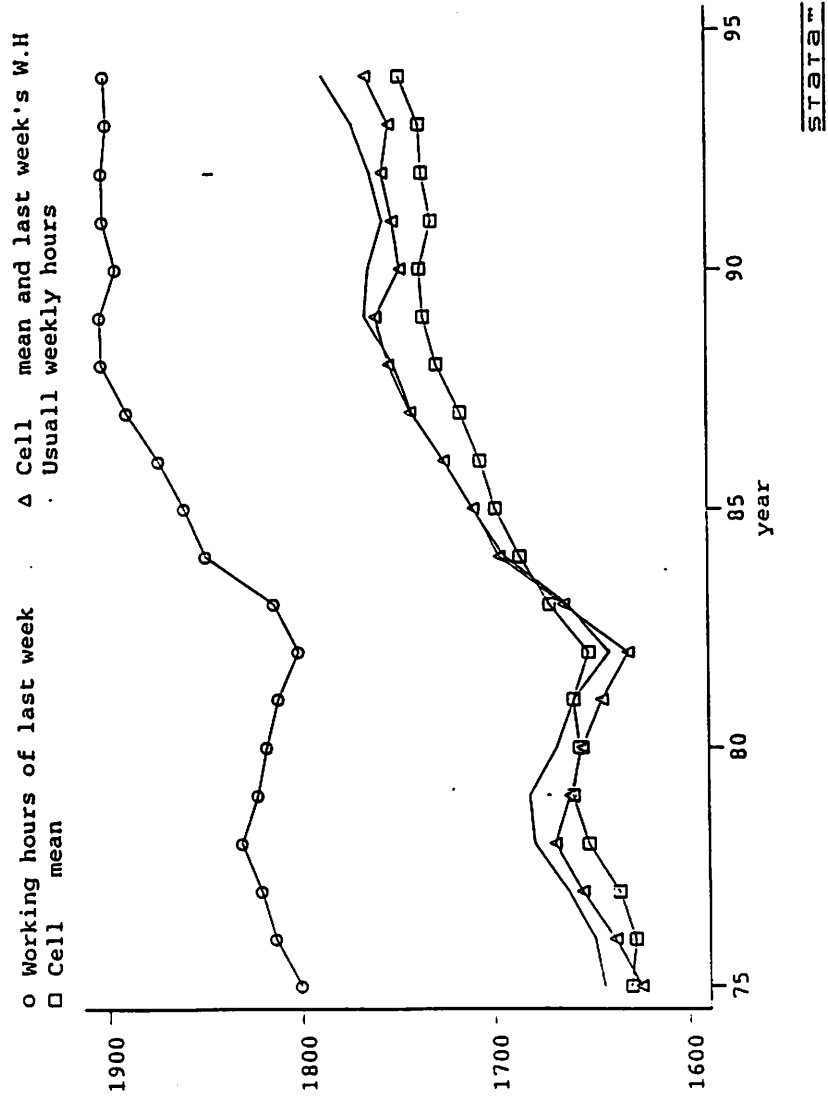
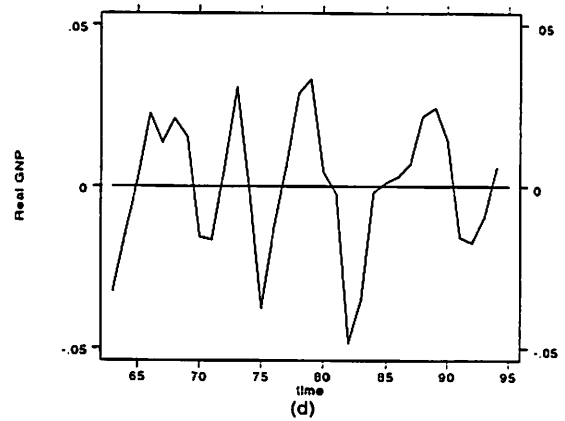
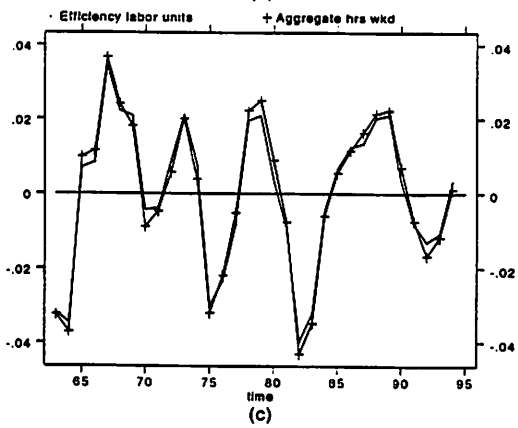
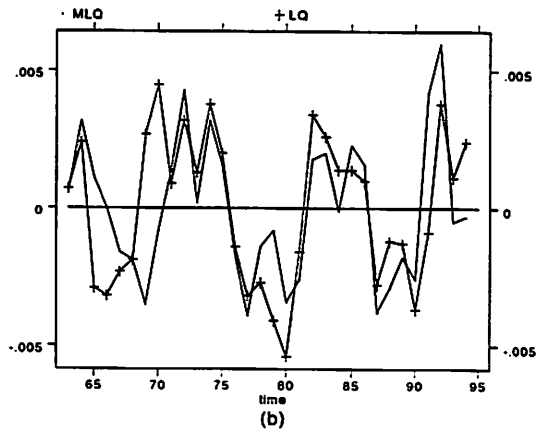
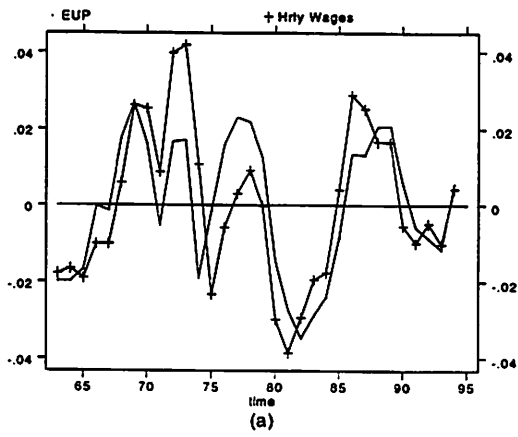


Figure 6: Various measures of Average Annual Working hours

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Non-self-employed workers, 1963-1994

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Figure 7: Cyclical variations in the annual data