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REAL WAGES OVER SHORT- AND LONG-TERM BUSINESS CYCLES: A TIME-SERIES EVIDENCE

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This paper examines the correlation between aggregate real wages and real activity over various horizons of business cycles. Using a frequency band filtering method, a business cycle indicator variable - the first difference of unemployment - is decomposed into high and low frequency components to represent short- and long-term business cycle movements, respectively. These components are used in real wage regressions to examine the characteristics of the correlation over various business cycle horizons. The main empirical findings of the study can be summarized as follows. 1) The real wage-real activity correlation has weakened significantly since 1980. 2) For the sample period 65:I - 79:IV, real wages vary procyclically during short-term business cycles, but are countercyclical over the long-term if the cutoff period is longer than five years. ii) Short-term movements of the cycle indicator induce asymmetric real wage movements. Positive movements of short-term unemployment have much stronger negative correlations with real wages than negative movements before 1980 but the converse holds after 1980. This suggests that real wages were more downwardly flexible and upwardly rigid before 1980 but became more upwardly flexible and downwardly rigid. 3) Supply driven cycle movements are more likely to induce countercyclical real wages than demand driven cycle movements before 1980 but the opposite is true after 1980.

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I. INTRODUCTION

The nature of the correlation between real wages and output has received a

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great deal of attention from numerous economists. While traditional IS-LM models predict a negative correlation between the two, empirical results show, in general, a weak positive correlation. When nominal wages are inflexible downward, a recession will induce a decrease in the price level and hence real wages will increase. Thus, the presence of the nominal wage rigidity is often investigated indirectly by analyzing the relationship between real wages and output. When the rational expectations hypothesis together with a nominal wage contract hypothesis are adopted in a model, such as in new Keynesian and new classical economic models, real wages are negatively correlated with unanticipated output movements. The majority of previous studies focused on simple contemporaneous regressions between real wages and business cycle proxies. The purpose of this study is to analyze the correlation between aggregate real wages and real activity over various horizons of business cycles. Often economic theories and models posit different short- and long-term relationships among economic variables. According to Shapiro and Watson (1988, p111), *"Standard textbook treatments of macroeconomic fluctuations separate the high frequency, business cycle fluctuations from the low frequency, growth fluctuations. This dichotomy lies at the heart of most Keynesian and rational expectations models."* [Italics added] As such, there is no a priori reason to believe that cyclical movements of real wages are the same over short- and long-term business cycles. The belief that labor supply may be unresponsive to short-term fluctuations of the economy but may be significantly responsive to long-term fluctuations leads us to suspect potentially different real wage-output correlations over various business cycle horizons.[1] Specifically, if labor supply is stable over the short-term but labor demand shifts, real wages will become procyclical. If, on the other hand, labor supply shifts significantly in response to long-term economic expectations, real wages can become countercyclical.

Neftci (1978) and Sargent (1978) were among the first to analyze the long-term relationship between real wages and the business cycle. Both of these studies found a long-term negative correlation.[2] Specifically, Neftci found that manufacturing employment has a positive contemporaneous correlation with the real wage, while lagged manufacturing employment has negative correlations. Thus, real wages are procyclical contemporaneously, but countercyclical over the long-term business cycle. This long-term negative correlation was partially refuted by Geary and Kennan (1982) who adopted Neftci's method and found no significant relationship when using the wholesale instead of consumer price index, to deflate nominal wages. Ensuing papers have not further distinguished the

[1] The definition of short- and long-term used in this paper is different from the conventional dichotomy. The definition is based on the frequency band decomposition of a stationary time-series, which is different from the conventional decomposition of a nonstationary series into stationary and nonstationary components.

[2] Sargent employs impulse response and variance decomposition techniques instead of the distributed lag model of Neftci.

long-term relationship from that obtained using short-term data.

More recent studies, especially those which use microdata, put primary focus on the contemporaneous correlations between real wages and cycle indicators.[3] The microdata studies found evidence of procyclical real wage movements, although the level of statistical significance varied. The procyclical results found in studies using both aggregate data and microdata lend credibility to the theories that stress the dominating role of labor demand shifts. Given that the real wage is only slightly procyclical, it must be that the labor demand curve shifts along a highly elastic effective labor supply curve (Hall (1988)). Yet there is evidence that the labor supply curve also shifts over time. For example, Ashenfelter and Card (1986) provide time-series evidence of substantial changes in the sex-age-race composition of the labor force over the long-term. Their results suggest that, with respect to the composition of the labor force, labor supply is stable over the short-term but changes significantly over the long-term. Blanchard and Quah (1989) and Shapiro and Watson (1988) assume that long-run output is determined by supply shocks, such as technology and labor supply. An implication of this assumption is that labor supply is more correlated with long-run output than with short-run output.

The purpose of this study is to analyze the correlation between aggregate real wages and real economic activity over short- and long-term business cycles. Three empirical models are used in this paper. The first model examines the correlations between real wages and short- and long-term movements of a business cycle proxy. The second model investigates the potential asymmetry in the real wage-business cycle correlations. In particular, the second model attempts to find whether the correlations during a downturn of the economy are different from the correlations during an upturn. The last model investigates whether demand shocks affect real wages differently than supply shocks. Specifically, I reexamine Sumner and Silver's (1989) results that imply aggregate supply shocks generate procyclical real wage movements, while aggregate demand shocks generate countercyclical movements.

The results reported in this paper are obtained using the first-difference of unemployment as the proxy variable for the business cycle. Using a filtering method, this proxy variable is decomposed into high and low frequency band components to represent short- and long-term business cycle movements, respectively. A set of cutoff frequencies (equivalently cutoff periods) are employed to define short- and long-term cyclical movements. The main empirical findings of this study can be summarized as follow: i) Real wages vary procyclically during

[3] Microdata was used to address the potential composition and selection biases present in aggregate data. Evidence suggests that the composition and selection biases counteract one another, making the benefits of using microdata appear tenuous. See Bils (1985), Keane, Moffit, and Runkle (1988), and Solon, Barsky, and Parker (1994), for further discussion of these biases. Other studies using microdata include Stockman(1983), Coleman(1984), Hashimoto and Raisian (1985), and Blank(1990).

short-term business cycles over all cutoff periods considered, but are countercyclical over the long-term if the cutoff period is longer than five years. ii) Short-term movements of the cycle indicator induce asymmetric real wage movements. Specifically, positive movements of short-term unemployment have much stronger negative correlations with real wages than negative movements which suggests that real wages are more downwardly flexible and upwardly rigid. iii) Demand driven cycle movements are more likely to induce countercyclical real wages than supply driven cycle movements. iv) Real wages became relatively more rigid, especially over economic downturns, during the 1980s and 1990s.

The rest of the paper is organized as follows. The following section describes the empirical model, section Ⅲ presents the empirical results, and section Ⅳ provides some concluding remarks.

Ⅱ. THE EMPIRICAL MODEL

The basic empirical model used in Bils (1985) and Solon et al. (1994) can be written as

$$w_t = \mu + \delta t + \beta \Delta U_t + \phi w_{t-1} + v_t \tag{1}$$

where $w_t = \Delta \ln W_t$, Δ denotes the first-difference operator, W_t is quarterly aggregate real wages, U_t is the quarterly unemployment rate, and v_t is an error ter m.[4] The use of first-differenced unemployment as the indicator of business conditions requires an explanation. First and most important, the time-series of U_t is very persistent and in fact the Dickey-Fuller unit root test does not reject the presence of a unit root. This implies that the spectral density of U_t is infinite at frequency zero and zero at other frequencies. Thus, an application of a frequency filtering for U_t does not make any sense. An easy way out of this difficulty is to adopt the most popular remedy, i.e., to use the first difference of U_t.[5] Since ΔU_t is stationary, its spectral density is not concentrated at a signle frequency and hence the application of frequency filtering will produce legitimate frequency components of ΔU_t.

A negative (positive) estimate of β of equation (1) indicates procyclical (countercyclical) movements of real wages. If $\{\Delta U_t : t = 1, \cdots\}$ is a purely nondeter-

[4] The lagged dependent variable is included to account for the first-order autocorrelation.

[5] Note that the first-differencing itself is a filtering. The spectral density of the first difference filter (see, for instance, Wei 1990) is not rectangular and hence it induces phase shifts and distorts the frequency characteristics of filtered outputs. Thus, the results reported in this paper can be influenced by the effects of the first-difference filtering. Unfortunately, a better filtering method than the first-differencing is not known to date.

ministic stationary process, it is endowed with the spectral representation,[6]

$$\Delta U_t = \int_{-\pi}^{\pi} e^{i\omega t} dz(\omega) \tag{2}$$

where $i = (-1)^{1/2}$, $dz(\omega)$ is a complex-valued random variable with

$$\begin{aligned} E[dz(\omega)dz(\lambda)^*] &= 0 & \text{if} \quad \omega \neq \lambda \\ &= s(\omega)d\omega & \text{if} \quad \omega = \lambda, \end{aligned}$$

$dz(\lambda)^*$ is the complex conjugate of $dz(\lambda)$, and $s(\omega)$ is the spectral density of ΔU_t. Equation (2) states that the random variable ΔU_t is the ensemble average over $[-\pi, \pi]$ of sines and cosines whose amplitude are determined by the complex-valued random variable $dz(\omega)$. Using equation (2), ΔU_t can be split into two components as

$$\begin{aligned} \Delta U_t &= \int_{\Omega^S} e^{i\omega t} dz(\omega) + \int_{\Omega^L} e^{i\omega t} dz(\omega) \\ &\equiv \Delta U_t^S + \Delta U_t^L \end{aligned} \tag{3}$$

where $\Omega^S = (-\pi, -a] \cup (a, \pi]$, $\Omega^L = [-a, a]$ for some $0 < a < \pi$. Since Ω^S denotes a high frequency band and Ω^L denotes a low frequency band, ΔU_t^S represents a high frequency (short-term) component, and ΔU_t^L represents a low frequency (long-term) component of ΔU_t. Using equation (2), equation (1) can be rewritten as

$$w_t = \mu + \delta t + \beta \int_{-\pi}^{\pi} e^{i\omega t} dz(\omega) + \phi\, w_{t-1} + v_t. \tag{1'}$$

Equation (1′) indicates that the parameter β represents the regression coefficient of the average frequency movements over $[-\pi, \pi]$ of ΔU_t. If the regression coefficient is different for different frequency movements of ΔU_t, equation (1′) can be represented in a more general form,

$$w_t = \mu + \delta t + \int_{-\pi}^{\pi} \beta(\omega) e^{i\omega t} dz(\omega) + \phi\, w_{t-1} + v_t \tag{4}$$

where $\beta(\omega)$ represents the correlation coefficient between w_t and movements of ΔU_t at frequency ω.[7] It is important to note that a comparison of equations (1) and (4) suggests that the usual regression coefficient β can be interpreted as the

[6] See, for instance, Granger and Newbold (1986) for the spectral representation.

[7] Equation (4) may be referred to as a frequency-varying parameter model.

average of the frequency-varying coefficients $\beta(\omega)$. Thus, it can be possible that β in equation (1) is statistically insignificant while $\beta(\omega)$ are positive and significant for some ω values but they are negative and significant for other ω values. In other words, the insignificant β can be the result of the canceling-out effect of positive and negative frequency-varying $\beta(\omega)$. This motivates this paper. If the statistical significance of $\beta(\omega)$ varies with frequency bands, it may shed new light on the characteristics of the U.S. business cycle.

Equivalently, equation (4) can be written as

$$w_t = \mu + \delta t + \int_{\Omega^S} \beta(\omega) e^{i\omega t} dz(\omega) + \int_{\Omega^L} \beta(\omega) e^{i\omega t} dz(\omega) + \phi\, w_{t-1} + v_t . \tag{4'}$$

The first integral represents the relationship between real wages and movements of ΔU_t over a high frequency band Ω^S, while the second integral represents the relationship over a low frequency band Ω^L. Let and β^L denote the *average* of over the frequency bands Ω^S and Ω^L, respectively. Then, equation (4') can be approximated as

$$w_t \cong \mu + \delta t + \beta^S \int_{\Omega^S} e^{i\omega t} dz(\omega) + \beta^L \int_{\Omega^L} e^{i\omega t} dz(\omega) + \phi\, w_{t-1} + v_t . \tag{5}$$

Using equation (3) and treating the approximation as an equality, equation (5) can be rewritten as

$$w_t = \mu + \delta t + \beta^S \Delta U_t^S + \beta^L \Delta U_t^L + \phi\, w_{t-1} + v_t . \tag{6}$$

Thus, the hypothesis that the relationship between real wages and short-term movements of ΔU_t is different from the relationship between real wages and long-term movements of ΔU_t can be examined if ΔU_t is filtered into two components which represent movements over frequency band Ω^S and Ω^L, respectively. The parameters β^S and β^L of equation (6) represent, respectively, the relationships between real wages and short-term (high frequency) and long-term (low frequency) movements of the first-difference of unemployment. A negative (positive) estimate of β^S or β^L will indicate procyclical (countercyclical) movements of real wages over short- or long-term business cycles, respectively. To estimate parameters in equation (6) ΔU_t should be filtered first.[8] Simple second-

[8] As is evident from equations (5) and (6), the estimates of β^S and β^L will be affected by any filter leakage since filter leakage affects the actual frequency band. Although the spectral-window filter of Cochrane (1989) and Sargent (1976) does not suffer from leakage, its use is unattractive in this situation because of the strong causal relation running from real wages to unemployment (employment) (Neftci (1978) and Sargent (1978)). Specifically, the regressors obtained from spectral-window filters will be correlated with the error term in equation (6), making the parameter estimators inconsistent.

order Chebyshev filters are used in this paper and the details on the filter construction as well as the filter coefficients are contained in the Appendix.[9]

Ⅲ. THE EMPIRICAL RESULTS

Using the Citibase data, variables from the sample period 64:I to 93:IV are selected for main empirical analysis.[10] Although manufacturing real wages are available from 47:I, 64:I is chosen as the starting quarter to facilitate the comparison of the results obtained from manufacturing real wages with those obtained from total real wages of nonagricultural industries which are available only from 64:I.[11] The results obtained from both the whole sample and a subsample (64:I - 80:IV) are reported to check for robustness, and to compare the results with those of previous studies including Bils (1985) and Sumner and Silver (1989). To save space, only the parameter estimates and their relevant statistics that are crucial for the main theme of the paper are reported. The details of the empirical results are available upon request.[12]

3.1. Symmetric Real Wage Movements

Table 1 reports the OLS results obtained from equation (6) in which real wages are measured as average hourly earnings of manufacturing deflated by the GNP deflator, and unemployment is measured by all unemployed workers.[13] The estimate -0.37 of β obtained with the unfiltered ΔU_t (the aggregate result) indicates procyclical movements of real wages for the whole sample periods. This result

[9] Unlike the spectral-window filters described in Cochrane (1989) and Sargent (1976), Chebyshev filters use only the current and past values of an input series. Thus, it does not make the parameter estimators in equation (6) inconsistent even though there exists a causal relation running from current real wages to future unemployment. The filter is not optimal, however, since it involves filter leakage.

[10] Citibase mnemonics are LEHM (average hourly earnings of manufacturing), LEH (average hourly earnings of production workers: total private nonagricultural), GNPQ (GNP in 1987 dollars), GD (GNP deflator), and LHUR (unemployment, all workers 16 years and older). All monthly data are averaged to yield quarterly observations.

[11] The comparison might be important since Blanchard (1987) finds much different time-series behavior between manufacturing real wages and total real wages of nonagricultural industries.

[12] Most of the regression models used in the paper are sound in the sense that regression errors do not show serial correlations in terms of the Ljung-Box Q statistics. The parameter estimates and the statistics that are not reported in the paper are available upon request.

[13] GNP deflator is used following Solon et al. (1994). It is known that the cyclicality of real wages is sensitive to the deflator chosen. Geary and Kenan (1982) found that real wages are more procyclical when deflated by the WPI, while Bodkin (1969) found that real wages are more procyclical when deflated by CPI. Sumner and Silver used real wages deflated by CPI arguing that consumption real wages should exhibit more procyclicality than product real wages (nominal wage deflated by WPI). Thus, the use of the GNP deflator as a price index will bias the results of this paper in a conservative direction.

is consistent with the findings of Bils (1985), Blank (1990), Keane et al. (1988), Solon et al. (1994), and Sumner and Silver (1989), among others. Similar results are obtained from short-term movements of the change in unemployment in that all of the estimates of β^S are negative and highly significant except for the two and three year cutoff periods.[14] As the cutoff period increases from 2 years the absolute value of the estimate and its significance level increase almost monotonically. These results suggest that real wages are procyclical with respect to short-term movements of unemployment.[15] The increase in absolute t-values as the cutoff period increases (except for the one year cutoff) seems to suggest the presence of real wage rigidity at typical business cycle frequencies.[16] If the countercyclical bias is not the sole reason for weak procyclicality for two and three year cutoff periods, the results indicate a sluggish adjustment of real wages over short-term business cycles.[17] The evidence of sluggish real wages over

[14] β^S and β^L are separately estimated throughout this paper to avoid a potential bias due to the multicollinearity between short- and long-term components of ΔU_t induced by the filter leakage. In fact, simple regressions suggest the existence of strong negative correlations between short- and long-term ΔU_t. When the short-term ΔU_t is regressed on the long-term ΔU_t, the slope estimate becomes negative for all cutoff periods considered and the adjusted R^2 approximates 0.35 except for the one year cutoff for which it approximates 0.19. Since the negative correlation between regressors induces a positive correlation between corresponding parameter estimators, the multicollinearity will make positive correlations between real wages and long-term components biased toward negative correlations. When both short- and long-term components are included in real wage regressions, the parameter estimates of the long-term components become positive for the cutoffs of seven years or greater but their t-values are not significant even at ten percent

Theoretically, the two components are orthogonal and hence separate regressions s hould not affect the parameter estimates. The correlation between filtered series is one of the weaknesses of nonoptimal filters.

[15] To check the robustness of the results against different filtering method, the following simple AR(1) filters are used to generate long-term cyclical movements: $\Delta U_t^L = \alpha \Delta U_{t-1}^L + x_t$ is ΔU_t and α varies from 0.90 to 0.99 in increments of 0.01. When the AR(1) filtered series are used for the whole sample period, the estimates of β^L range from 0.0003 to 0.0005 and their t-values vary from 1.13 to 1.35 for. Although the results are not statistically significant the countercyclicality of real wage is supported. Note that the small parameter estimates are mainly due to the amplitude distortion induced by AR(1) filters. The robustness is also checked with first-differenced cycle variables, i.e., with $\Delta^2 U_t$. Since the first-differencing eliminates the low-frequency component, the first-differenced series can be a crude proxy for the short-term component. When $\Delta^2 U_t$ is used for the entire sample, the estimates of β^S becomes -0.0047 (-2.87)**. Therefore, the results confirm the procyclicality with respect to short-term movements of cycle variables. The subsample period 64:I - 80:IV provides consistent results.

[16] Table 9.1 of Abel and Bernanke (1992) shows that since 1960, a typical business cycle contraction lasts less than 1.5 years. This implies that most economic downturns in these samples are represented in the short-term, specifically with a three year cutoff.

short-term business cycles becomes weaker when manufacturing real wages are substituted by total real wages of nonagricultural industries. The estimates (t-values) of at two and three year cutoffs become -0.30 $(-1.95)^{+}$ and -0.24 $(-3.07)^{**}$, respectively, where superscripts + and ** denotes statistical significance at 10 percent and one percent, respectively. Thus the results suggest that real wages are more rigid in the manufacturing than non-manufacturing over two and three year business cycle frequencies.

When long-term movements are analyzed, the estimates of β show a much different pattern. At cutoffs of five years and greater, the estimates are positive but not statistically significant which suggests that there is a tendency for real wages to move countercyclically over long-term business cycles. This finding is consistent with the results of Neftci (1978) who shows that the evidence of countercyclicality becomes stronger as more lags are used in his model.[18]

The finding that real wages are procyclical over short-term business cycles but countercyclical over long-term business cycles may suggest the fact that short-term cycles are mainly driven by perturbations in the labor demand schedule while long-term cycles are mainly driven by perturbations in the labor supply schedule. Thus, this finding can provide a convenient framework for the macroeconomic identification of demand and supply perturbations. More research is needed to be able to exploit the finding in building new macroeconomic theories.

In order to examine the possibility of a break in the relationship between real wages and the business cycle indicator, equation (6) is modified to

$$w_t = \mu + \delta t + \beta_1^S D_{1t} \Delta U_t^S + \beta_2^S D_{2t} \Delta U_t^S + \beta_1^L D_{1t} \Delta U_t^L + \beta_2^L D_{2t} \Delta U_t^L + \phi\, w_{t-1} + v_t \quad (7)$$

where D_{1t} and D_{2t} denote dummy variables where D_{1t} equals 1 for 1965:I to 1979:IV and 0 for 1980:I to 1997:II and D_{2t} equals 0 for 1965:I to 1979:IV and 1 for 1980:I to 1997:II. Thus, equation (7) can capture a break in the slope coefficients β^S and β^S at 1980:I.[19] The choice of the timing of a break reflects the change in the operating procedure of the Federal Reserve in the fourth quarter of 1979 and it divides the sample approximately into one half.

Table 2 contains the regression results of equation (7). The first panel shows the results obtained from unfiltered aggregate business cycle indicator ΔU_t. For

[18] Following Neftci, when the growth rate of manufacturing employment is used as the cycle indicator and GNP inflation is used to deflate nominal wages over the period 48:I - 71:IV, procyclical real wage movements become countercyclical as the cutoff period of *short-term* movements is increased. Weaker results are obtained with the use of CPI as the deflator. All short-term, including the unfiltered aggregate, movements of manufacturing employment have significant (at less than 10% except for 2 year cutoff) positive correlations with real wages. However, the positive correlations become negative when long-term components are used (estimates are significant at 10% for 4, 9, and 10 year cutoffs, at less than 5% for 5 to 7 year cutoffs).

[19] An intercept dummy was also tried but was found to be insignificant.

the first sample period, 65:I - 79:IV, the estimate is -0.57 with the absolute t-value 3.50. For the second sample period, 80:I - 97:II, it is -0.18 with the absolute t-value 2.05. The result suggests a significant change in movements in real wages over the business cycles. Before 1980, real wages were strongly procyclical, a one percent reduction in unemployment would increase real wages by 0.57 percent which is significant at less than one percent. In contrast, after 1980, a one percent reduction in unemployment would increase real wages by only 0.18 percent which is significant only at five percent. The signifiant decrease in the size of the coefficient indicates that real wages were much more procyclical before 1980 than they were after 1980. The evidence for the break is also evident in the results obtained from filtered cycle indicators. The first column of the second panel shows that short-term cycle indicators are significant at five percent for four and five year cutoffs and at one percent for six to ten year cutoffs. Short-term real wages are procyclical and the strength of procyclicality increases as the cutoff period increases. Contray to the results in the first column, the results in the second column indicate the countercyclicality of real wages with respect to long-term movements of unemployment. While the cutoff periods of 1, 2, and 3 years induce procyclical real wage movements, the cutoff period greater than 5 years induce significant countercyclical real wage movements. Much different results are obtained from the second sample period. As can be seen from the third column, short-term movements of the cycle indicator do not induce significant procyclical real wage movements. Only the cutoff periods, 1, 4, 8, 9, and 10 make procyclical movements significant at 10 percent. This suggests that real wages have become significantly more inflexible over the businsess cycles after 1980. Consistent evidence is in the last column. Unlike the results in the second column, real wages cease to be countercyclical after 1980. Total real wages provide consistent but stronger evidence (not reported) for a break in 1980. The absolute t-values when total real wages are used are in general greater than those reported in Table 2. Greater absolute t-values make all estimates of β_2^S significant at least at five percent. However, none of the estimates of β_2^L are statistically significant which indicates total real wages also cease to be countercyclical after 1980.

3.2. Asymmetric Real Wage Movements over Short-term Business Cycles

The significant procyclical movements of real wages over short-term business cycles pose an interesting question: Are the real wage movements symmetric over positive and negative movements of the cycle variable? If real wages are short-term movements of $\Delta U_t(\Delta U_t^S)$ are decomposed into positive and negative components as follows.[20]

$$\Delta U_t^{SP} = (1/2)[\,|\Delta U_t^S| + \Delta U_t^S]$$
$$\Delta U_t^{SN} = -(1/2)[\,|\Delta U_t^S| - \Delta U_t^S]$$

where $|\,.\,|$ is the absolute value operator.[21] $\Delta U_t^{SP}(\Delta U_t^{SN})$ equals ΔU_t^s if ΔU_t^S is positive (negative) and zero otherwise. Real wage responses to the movements of ΔU_t^{SP} and ΔU_t^{SN} are examined using the equation,

$$w_t = \mu + \delta t + \beta^{SP}\Delta U_t^{SP} + \beta^{SN}\Delta U_t^{SN} + \phi\, w_{t-1} + v_t\,. \tag{8}$$

Table 3 presents the OLS results for equation (8) for two sample periods.[22] The top panel contains the estimates of β^P and β^N of the positive and negative components of the aggregate (unfiltered) ΔU_t. For the whole sample period, positive aggregate movements of ΔU_t are highly significant while negative movements are not indicating downward real wage flexibility. The estimate -0.48 of β^{SP} suggests that a one percent increase in unemployment will cause 0.48 percent drop in real wages. A one percent decrease in unemployment, however, increases real wages by only 0.15 percent which is not statistically significant as can be seen from the estimate of β^{SN}. For the subsample period 80:I - 97:II, neither β^{SP} nor β^{SN} is significant indicating aggregate real wages became rigid for both directions after 1980. This is consistent with the results in the top panel of Table 2 in that real wages have become less responsive to unemployment fluctuations since 1980. The first column of Table 3 shows that for the whole sample period real wages were procyclical with respect to positive short-term movements of unemployment for cutoff periods greater than 3 years. This indicates that when unemployment is rising real wages go down. However, the insignificant parameter estimates for the two and three year cutoffs again suggest the presence of real wage rididity over business cycle frequencies that include typical economic downturns. A comparison of the parameter estimates of the positive and negative components reveals that generally a decrease in real wages during an economic downturn (first column) is larger than the increase in

[20] Since long-term components are highly persistent, the positive and negative decomposition of long-term components may not be very interesting. Nevertheless, when positive and negative long-term components are used, real wages become countercyclical when the cutoff equals four years for both positive and negative components of unemployment. The estimates are significant at five percent when the cutoff becomes six (eight) years for positive (negative) movements.

[21] Cover (1992) uses the same decomposition for the analysis of asymmetric effects of money supply.

[22] To avoid the potential multicollinearity problem between positive and negative short-term components, each component is separately used as a regressor in equation (7).

real wages during an economic upturn (second column). In particular, the results in the second column suggest that negative short-term movements of unemployment do not induce significant procyclical real wage movements. This tells that real wages are downwardly flexible but upwardly rigid. After 1980, however, real wages became downwardly rigid but upwardly flexible as can be seen from third and fourth columns of the table. The results in the third column indicate that real wages do not significantly respond to increases in unemployment regardless of the cutoff period (one and three cutoffs are exceptions). In contrast, the fourth column suggests that the responses of real wages are significant at least at 10 percent except for the 10 year cutoff. Thus, the direction to which real wages are rigid and flexible has changed since 1980.

When total real wages of nonagricultural industries are substituted for manufacturing real wages, consistent but slightly different evidence for asymmetry emerges (results are not shown). A comparison of the estimates of β^{SP} and β^{SN} indicates that total real wages yield larger estimates of both β^{SP} and β^{SN}. Also, total real wages make absolute t-values of the estimates of β^{SP} and β^{SN} larger so that most β^{SP} and β^{SN} estimates are now significant at one percent. This suggests that total real wages decline more than manufacturing real wages during an economic downturn, and the former increases more during an economic expansion. In other words, manufacturing real wages are more rigid downward and upward.

An interesting pattern that emerges from the analysis of total real wages is that they became much more rigid over the business cycle downturns than over the business cycle upturns during the 1980s and 1990s. For instance, with 3 year cutoff, the estimate (absolute t-value) of β^{SP} is -0.53 (2.12) for the whole sample but it becomes -0.19 (1.50) for 80:I - 97:II. In contrast, β^{SN} is -0.31 (3.57) for the whole sample and -0.37 (3.15) for 80:I - 97:II. With ten year cutoff, β^{SP} is -0.84 (5.45) and -0.36 (2.72) while β^{SN} is -0.44 (2.78) and -0.23 (2.35). Thus, the decrease in the absolute size of the estimates (and their absolute t-values) of β^{SP} is larger than that of β^{SN}. A comparison of the results obtained from manufacturing real wages with those obtained from total real wages suggests that the former became more rigid over the business cycle downturns after 1980 than the latter. An evidence to this is that while most estimates of β^{SP} for the 80:I - 97:II period are not significant when manufacturing real wages are used, they become significant at least at five percent (2 and 3 year cutoffs are an exception) when total real wages are used.

3.3. The Effect of Aggregate Demand and Supply on Real Wages

This section examines whether the finding that real wages are procyclical predominantly during economic downturns reflect the effects of supply shocks. Sumner and Silver (1989) argue that if nominal wages are sticky, cycles driven by demand shocks should lead to countercyclical real wage movements, while cycles driven by supply shocks should lead to procyclical real wage movements. To examine the effects on real wages of short-term movements on output, driven either by demand or supply shocks, the following vector autoregression (VAR) model is adopted.[23]

$$X_t = \mu + \sum_{i=1}^{S} \Phi_i X_{t-i} + \varepsilon_t \tag{9}$$

where $X_t = [\Delta\pi_t \; \Delta ln\,GNP_t]'$, μ is an intercept vector, Φ_i are unknown parameter matrices, $\varepsilon_t = [u_t \; v_t]'$, and u_t and v_t are white noise errors.[24] The estimates of u_t and v_t are used as inflation and GNP growth shocks, respectively. The identification of aggregate demand and aggregate supply shocks are based on the sign of the product of u_t and v_t. A positive sign of the product $u_t v_t$ is assumed to be demand driven shocks, whereas a negative sign is assumed to be supply driven shocks.[25] Specifically, the identification is based on the following equations.

$$\begin{aligned} I_t^D &= (1/2)(1 + u_t v_t / |u_t v_t|) \\ I_t^S &= (1/2)(I - u_t v_t / |u_t v_t|) \\ \Delta U_t^{SD} &= I_t^D \Delta U_t^S \\ \Delta U_t^{SS} &= I_t^S \Delta U_t^S \end{aligned} \tag{10}$$

where I_t^D and I_t^S denote indicator functions for demand and supply shocks, respectively, and ΔU_t^{SD} and ΔU_t^{SS} denote short-term movements of ΔU_t that are driven by a demand shock and by a supply shock, respectively.[26] The demand shock indicator I_t^D takes the value 1 if the product $u_t v_t$ is positive, i.e., if innovations in inflation and GNP growth have the same sign, and takes 0 otherwise. For example, ΔU_t^{SD} is equal to ΔU_t^s if the demand shock indicator is

[23] Long-term movements of unemployment were also decomposed into demand and supply driven components and used in the regressions. However, most of the results were insignificant and hence they are not reported.

[24] The first-difference of inflation $\Delta\pi_t$ is used because the Dickey-Fuller test shows nonstationarity in π_t. The lag-length 8 is selected since $\Delta ln\,GNP_{t-7}$ is significant at 10 percent in the $\Delta\pi_t$ equation, and $\Delta\pi t-5$ is significant at 10 percent in the $\Delta ln\,GNP_t$ equation. Almost the same results obtain as those presented when the lag length is increased to 12.

[25] The identification restriction follows one of the stylized facts of the business cycle described in Blanchard (1989) and Gali (1992).

[26] An alternative way of identifying demand- and supply-driven movements is to use the sign of the product of $\Delta\pi$ and ΔU as is done in Sumner and Silver (1989). Although qualitatively the same results obtain as those reported below, we believe the identification based on "shocks" is more appealing since the identification method of Sumner and Silver can not discriminate current innovations from movements due to the effect of previous shocks.

unity, and is equal to zero otherwise.

To check that the economic shocks are properly identified, a time-series plot of innovations in GNP growth, obtained from equation (9), is presented in Figure 1. Shaded areas indicate supply driven periods obtained from equation (10). The figure shows that supply shocks were dominant during the early and mid 1970s but demand shocks dominated during the late 1970s and early 1980s. In particular, the figure suggests that the 1974 recession was supply driven, but the 1982 recession was demand driven. It also suggests that the recession during the first and second quarter of 1980 was supply driven. Thus, the identified periods are consistent, in general, with the two well-known oil price shocks and subsequent recessions.

As a rough diagnostic check on the above identification method, demand and supply driven inflation and GNP growth are regressed on the four lags of the growth rate of the real price of oil.[27] The exclusion tests of the four lags of oil suggest that the oil variable predicts both the demand and supply driven movements in inflation but the F statistic for supply driven movements (8.229) is almost twice that of demand driven movements (4.404). When the same tests are applied to the regressions of GNP growth, the F statistic for demand driven GNP movements is not significant (p-value 0.82), while that of the supply driven GNP movements is highly significant (p-value 0.0004).[28] Therefore, the results support the identification method in that the oil variable is more significant for supply driven movements than for demand driven movements of inflation and GNP growth.

The response of real wages to aggregate demand and supply shock driven short-term movements of the cycle indicator is examined using the equation,

$$w_t = \mu + \delta t + \beta^{SD} \Delta U_t^{SD} + \beta^{SS} \Delta U_t^{SS} + \phi\, w_{t-1} + v_t \tag{11}$$

where ΔU_t^{SD} and ΔU_t^{SS} are defined in equation (10) above. When demand and supply driven aggregate (unfiltered) ΔU_t are used in (11), the estimates (absolute t-values) of β^D and β^S become -0.31 (4.13) and -0.45 (2.43) for the entire sample period, and -0.17 (2.42)* and 0.02 (0.11) for the period 80:I - 97:II. These results suggest that procyclical real wage movements are present for both demand and supply driven movements of unemployment before 1980. Since 1980, however, the procyclicality has substantially weakened. In terms of the size of the coefficient estimate, supply (demand) driven components induce

[27] The growth rate of the real price of oil is obtained following Mork (1989) , details are available upon request.

[28] The demand and supply driven inflation and GNP growth are obtained from slightly different indicator functions from those defined in (7). Namely, the new indicator functions convert the zero values of I_t^D and I_t^S into missing observations. Thus, the dependent variable does not contain artificially generated zero values.

stronger procyclical real wage movements before (after) 1980. Also the results indicate that real wage movements became insignificant with respect to the supply driven movements of unemployment after 1980. Thus, the aggregate results provide evidence that the pattern of the response of real wages to demand and supply driven components has significantly changed since 1980. The results indicate that real wages became more rigid after 1980 with respect to demand and supply driven output movements.

The results of short-term unemployment movements differ depending upon whether they are demand or supply driven.[29] Specifically, the movements of real wages are found to be procyclical during 65:I - 79:IV with respect to short-term movements of unemployment (first and second columns) irrespective of whether the shocks are demand or supply driven. This result contradicts Sumner and Silver's (1989) argument that demand shocks should generate countercyclical real wage movements, while supply shocks should generate procyclical movements. Consistent with evidence provided above, real wages were rigid over 2 and 3 year business cycles before 1980 regardless of whether they are demand or supply driven. Since 1980, demand driven cyclical movements have become the dominant factor that drives procyclical wage movements. While all estimates in the third column are significant at least at 10 percent, not a single estimate in the fourth column is significant at the same level. Thus, supply shocks have become much less important for real wage movements. Although the size of coefficient estimates of β^{SD} has decreased (in absolute value) since 1980, their absolute t-values have increased substantially. It is interesting to note that the real wage rigidity over the typical business cycle downturns has almost disappeared since 1980 since the estimates of β^{SD} for 2 and 3 year cutoffs are significant at least at 10 percent. Overall, the results in Table 4 indicate the existence of asymmetry in the wage-unemployment correlation depending upon whether the movements in unemployment are demand or supply driven.

IV. CONCLUDING REMARKS

This paper examined the characteristics of the movement of real wages over various horizons of the business cycle. The main focus of the study is on the correlation between the movements of real wages and a set of different frequency movements of business cycle indicators. It was found that real wages move procyclically over the short-term but countercyclically over the long-term business cycle. The statistical evidence for procyclical movements of real wages is weak for short-term movements with two and three year cutoffs. This suggests that real wages have been rigid during typical economic downturns of the postwar period. The presence of potential asymmetries in the correlation

[29] To avoid potential multicollinearity, the results are obtained using demand and supply shock components separately in the regression.

between real wages and cycle indicators was also examined. The results suggest that manufacturing real wages are more downwardly flexible and upwardly rigid over short-term business cycles. Cycle movements were then identified either as demand driven or supply driven. The evidence on correlations between real wages and these two components indicates that demand driven cycle movements are more likely to induce procyclical real wages than supply driven cycle movements.

To test a potential break in the relationship, the analysis was performed using time dummies that are multiplied to the cycle indicators. The results suggest that there has been a statistically significant break in 1980 in the real wage-unemployment relationship. The procyclicality of real wages have been much stronger during 1965:I - 1979:IV than during 1980:I - 1997:II. During the latter sample period, real wages have become more inflexible over most of the high and low frequencies examined. In particular, the countercyclical real wage movements over the long-term business cycles have weakened completely since 1980. Also the evidence of procyclical real wage movements became tenuous after 1980. The results were generally consistent with the findings reported herein, with the additional finding that overall, real wages became more rigid during the 1980s and 1990s. In particular, it was found that the rise in rigidity was greater over economic downturns than over economic upturns. Whether this rise in downward rigidity contributed to the increase in the overall level of unemployment during the 1980s is an interesting question for future research. When the growth rate of GNP was used as the cycle indicator, statistically weaker but qualitatively the same results were obtained (results are available upon request).

The correlation between real wages and the business cycle, and any asymmetries in that correlation, were reexamined using the total real wage of nonagricultural industries instead of the manufacturing real wage. In reexamining the basic correlation, it was found that the absolute t-values of total real wages are greater than those of manufacturing real wages, suggesting that real wages are more rigid in the manufacturing sector. When total real wages were substituted for manufacturing wages, consistent evidence for asymmetry emerged. The results suggest that during an economic downturn total real wages decline more than manufacturing real wages, but during an economic upturn, total real wages increase more than manufacturing real wages. In other words, manufacturing real wages are more rigid both downward and upward than non-manufacturing real wages.

Appendix

1. Construction of Chebyshev Filters

The low and high pass Chebyshev filters are characterized by four parameters: The size of pass-band ripple, the stop frequency, the speed of frequency attenuation, and the cutoff frequency. In general, the necessary procedure involving the construction of an appropriate discrete time low pass Chebyshev filter can be summarized in six steps.[30] The following description relies on the details of Ludeman (1986, p175-179) that are provided for the construction of Butterworth filters.[31]

1.1 Construction of Low Pass Chebyshev Filter

Step 1: Convert the discrete time cutoff frequency and stop frequency into continuous time equivalents by a tangent transformation:

$$\Omega_c = 2\tan(\omega_c/2) \quad \text{and} \quad \Omega_s = 2\tan(\omega_s/2) \tag{A.1}$$

Step 2: Determine the order n of the Chebyshev filter from:

$$n = \left[\frac{\log_{10}[g + (g^2-1)^{1/2}]}{\log_{10}[\Omega_r + (\Omega_r^2 - 1)^{1/2}]} \right]_+$$

where

$$g = \left[\frac{A^2-1}{\varepsilon^2} \right]^{1/2}, \quad \Omega_r = \Omega_s/\Omega_c, \quad A = 1/|H(i\Omega_r)|$$

$[.]_+$ denotes the smallest integer larger than the value inside the bracket, and $i = \sqrt{-1}$. For example, an acceptable pass band ripple $1 - 1/(1+\varepsilon^2) = 0.10875$, a speed of attenuation $1/A^2 = 0.07$ at the stop frequency $\omega_s = 2\pi/4$, and the cutoff frequency $\omega_c = 2\pi/8$ result in the filter order $n = 2$.

Step 3: Determine the normalized (i.e., unit pass band) Chebyshev low pass filter $H_n(s)$ based on the ripple characteristic ε^2 and the order n

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[30] A Lotus file which calculates the coefficients of second-order Chebyshev filters with the same ripple and attenuation characteristics as described in the Appendix is available from the author.

[31] The reason that Chebyshev filters are used instead of Butterworth's is to exploit the smaller transition band (i.e., the leakage band) of Chebyshev's for a given filter order. This smaller transition band is achieved by allowing the pass-band ripple.

obtained in Step 2:

$$H_n(s) = \frac{K_n}{V_n(s)} \tag{A.2}$$

where

$$\begin{aligned} K_n &= b_0/\sqrt{1+\varepsilon^2} \quad \text{for n even} \\ &= b_0 \qquad\qquad\quad \text{for n odd} \\ V_n(s) &= s^n + b_{n-1}S^{n-1} + \cdots + b_1 s + b_0. \end{aligned}$$

Note that the parameters $b_{n-1}, \cdots, b_0$ can be obtained from Table 3.4 of Ludeman (1986, p140-141).

Step 4: Now the above normalized low pass filter should be transformed to obtain one with a cutoff frequency Ω_c by substituting s by s/Ω_c:

$$H_L(s) = H_n\left(s \rightarrow \frac{s}{\Omega_c}\right)$$

where the notation (a⟶b) denotes the substitution of b for a.

Step 5: The continuous time low pass Chebyshev filter $H_L(s)$ is converted into a discrete time low pass filter $H_L(z)$ using a bilinear transformation:[32]

$$H_L(z) = H_L\left(s \rightarrow 2\frac{1-z^{-1}}{1+z^{-1}}\right).$$

Step 6: The filter function $H_L(z)$ is used to obtain the time domain filter by the inverse Z transform. For instance, when $X(z)$ and $Y(z)$ denote the Z transforms of input series $\{x_t\}$ and output series, $\{y_t\}$, $H_L(z)$ has the following relationship:

$$H_L(z) = \frac{Y(z)}{X(z)}$$

For instance, a second-order Chebyshev low pass filter with cutoff period of eight quarters can be written as:

[32] See, for instance, Oppenheim and Schafer (1975) and Ludeman (1986) for the bilinear transformation.

$$y_t = 0.799568\, y_{t-1} - 0.361833\, y_{t-2} + 0.132703(x_t + 2x_{t-1} + x_{t-2})$$

where $\{y_t\}$denotes the filtered series of $\{x_t\}$.[33]

1.2 Construction of High Pass Chebyshev Filter

When the above pass band ripple and attenuation characteristics are maintained, the corresponding high pass filter with discrete time cutoff frequency ω_H can be obtained first by converting ω_H into a continuous time cutoff frequency Ω_H by equation (A.1), and secondly by substituting s in equation (A.2) with Ω_H/s. That is, the high pass filter function can be obtained from:

$$H_H(s) = H_n\left(s \rightarrow \frac{\Omega_H}{s}\right). \tag{A.3}$$

Note that equation (A.3) is similar to Step 4 above. The required discrete time domain filter function can be obtained by following Step 5 and Step 6 above. For example, a high pass filter with an eight quarter cutoff period can be obtained by:

$$y_t = 1.180386\, y_{t-1} - 0.481617\, y_{t-2} + 0.628273(x_t - 2x_{t-1} + x_{t-2})$$

where $\{y_t\}$ denotes the filtered series of $\{x_t\}$.[34]

2. Filter Coefficients Used in the Text

The second-order *high pass* Chebyshev filters are in the form

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \alpha_3(x_t - 2x_{t-1} + x_{t-2})$$

and the *low pass* filters are in the form

$$y_t = \beta_1 y_{t-1} + \beta_2 y_{t-2} + \beta_3(x_t + 2x_{t-1} + x_{t-2}).$$

[33] The low pass filter can be initialized by the sample mean.

[34] The mean of high pass filter is zero. Thus, the filter can be initialized by using zeros.

Cutoff in years	α_1	α_2	α_3	β_1	β_2	β_3
1	0.26191	−0.27667	0.36313	−0.26191	−0.27667	0.36313
2	0.18039	−0.48162	0.62827	0.79957	−0.36183	0.13270
3	0.14664	−0.61219	0.72659	1.19548	−0.48755	0.06893
4	1.60561	−0.69166	0.77821	1.39277	−0.57788	0.04215
5	1.68766	−0.74444	0.81003	1.52230	−0.64268	0.02841
6	1.74163	−0.78191	0.83161	1.60420	−0.69079	0.02044
7	1.77980	−0.80985	0.84721	1.66246	−0.72772	0.01540
8	1.80818	−0.83147	0.85901	1.70596	−0.75689	0.01202
9	1.83012	−0.84869	0.86825	1.73962	−0.78048	0.00964
10	1.84756	−0.86272	0.87568	1.76644	−0.79993	0.00790

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[Table 1] Estimates of β^S and β^L of the Regression

$$w_t = \mu + \delta t + \beta^S \Delta U_t^S + \beta^L \Delta U_t^L + \phi\, w_{t-1} v_t$$

where w_t denotes the growth rate of manufacturing real wages, t denotes a time index, and $\Delta U_t^S(\Delta U_t^L)$ denotes short-term (long-term) component of the first-difference of unemployment ΔU_t.

Data period: 1965:I - 1997:II

	β	
Aggregate	-0.37 (3.59)**	

Cutoff in years	β^S	β^L
1	−0.79 (2.83)**	−0.18 (2.15)**
2	−0.23 (1.05)	−0.23 (2.62)**
3	−0.24 (1.50)	−0.17 (2.00)*
4	−0.49 (2.83)**	−0.05 (0.48)
5	−0.36 (2.74)**	0.09 (0.67)
6	−0.39 (2.87)**	0.20 (1.17)
7	−0.41 (2.90)**	0.30 (1.34)
8	−0.43 (2.97)**	0.39 (1.42)
9	0.44 (3.04)**	0.47 (1.50)
10	0.44 (3.13)**	0.55 (1.59)

Numbers in parentheses denote absolute t-values that are based on the Newey-West autocorrelation and heteroskedasticity consistent covariance matrix estimators. Superscripts +, *, and ** denote statistical significance at 10%, 5%, and 1%, respectively.

[Table 2] Estimates of β^S and β^L of the Regression

$$w_t = \mu + \delta t + \beta^S \Delta U_t^S + \beta^L \Delta U_t^L + \phi\ w_{t-1} v_t$$

where w_t denotes the growth rate of manufacturing real wages, t denotes a time index, and $\Delta U_t^S(\Delta U_t^L)$ denotes short-term (long-term) component of the first-difference of unemployment .

	65:I - 79:IV	80:I - 97:II
Aggregate	-0.57 (3.50)**	-0.18 (2.05)*

	65:I - 79:IV		80:I - 97:II	
Cutoff in years	β^S	β^L	β^S	β^L
1	−0.93 (1.62)	−0.32 (5.31)**	−0.65 (3.25)**	−0.04 (0.36)
2	−0.25 (0.60)	−0.38 (9.26)**	−0.21 (1.57)	−0.09 (0.86)
3	−0.35 (1.14)	−0.23 (2.70)**	−0.12 (0.94)	−0.11 (0.94)
4	−0.75 (2.09)*	0.02 (0.15)	−0.21 (1.89)+	−0.11 (0.92)
5	−0.60 (2.38)*	0.28 (1.58)	−0.10 (1.09)	−0.10 (0.72)
6	−0.66 (2.61)**	0.52 (2.52)*	−0.12 (1.37)	−0.07 (0.42)
7	−0.69 (2.75)**	0.75 (3.12)**	−0.14 (1.55)	−0.03 (0.14)
8	−0.71 (2.82)**	0.93 (3.30)**	−0.17 (1.83)+	0.03 (0.12)
9	−0.71 (2.95)**	1.04 (3.03)**	−0.20 (2.05)*	0.11 (0.35)
10	−0.68 (3.20)**	1.10 (2.56)**	−0.22 (2.27)*	0.21 (0.59)

Numbers in parentheses denote absolute t-values that are based on the Newey-West autocorrelation and heteroskedasticity consistent covariance matrix estimators. Superscripts +, *, and ** denote statistical significance at 10%, 5%, and 1%, respectively.

[Table 3] Estimates of β^{SP} and β^{SN} of the Regression

$$w_t = \mu + \delta t + \beta^{SP} \Delta U_t^{SP} + \beta^{SN} \Delta U_t^{SN} + \phi\ w_{t-1} v_t$$

where w_t denotes the growth rate of manufacturing real wages, t denotes a time index, and $\Delta U_t^{SP} (\Delta U_t^{SN})$ denotes positive (negative) movements of the short-term component ΔU_t^S of ΔU_t.

	65:I - 97:IV		80:I - 97:II	
	β^{SP}	β^{SN}	β^{SP}	β^{SN}
Aggregate	-0.48 (3.14)**	-0.15 (0.86)	-0.16 (1.32)	-0.06 (0.38)

	65:I - 97:IV		80:I - 97:II	
Cutoff in years	β^{SP}	β^{SN}	β^{SP}	β^{SN}
1	−1.01 (2.48)*	−0.59 (2.92)**	−0.57 (1.85)	−0.69 (2.83)**
2	−0.11(0.31)	−0.32 (1.29)	0.19 (1.13)	−0.57 (2.69)**
3	−0.19 (0.59)	−0.18 (1.21)	0.31 (1.70)+	−0.55 (3.22)**
4	−0.66 (3.00)**	−0.37 (1.54)	−0.05 (0.26)	−0.34 (1.92)+
5	−0.62 (2.39)*	−0.15 (1.16)	0.22 (1.12)	−0.39 (2.67)**
6	−0.61 (2.99)**	−0.20 (1.31)	0.11 (0.64)	−0.30 (2.37)*
7	−0.61 (3.36)**	−0.23 (1.30)	0.07 (0.39)	−0.27 (2.28)*
8	−0.64 (3.54)**	−0.24 (1.26)	−0.06 (0.42)	−0.21 (1.87)+
9	−0.66 (3.46)**	−0.25 (1.23)	−0.15 (0.99)	−0.17 (1.65)+
10	−0.68 (3.31)**	−0.23 (1.11)	−0.21 (1.33)	−0.15 (1.36)

Numbers in parentheses denote absolute t-values that are based on the Newey-West autocorrelation and heteroskedasticity consistent covariance matrix estimators. Superscripts +, *, and ** denote statistical significance at 10%, 5%, and 1%, respectively.

[Table 4] Estimates of β^{jD} and β^{jS} of the Rregression

$$w_t = \mu + \delta t + \beta^{jD} \Delta U_t^{SD} + \beta^{jS} \Delta U_t^{SS} + \phi\ w_{t-1} v_t$$

where w_t denotes the growth rate of manufacturing real wages, t denotes a time index, $\Delta U_t^{SD}(\Delta U_t^{SS})$ denotes demand (supply) driven movements of the short-term component of ΔU_t.

	65:I - 79:IV		80:I - 97:II	
	β^{SD}	β^{SS}	β^{SD}	β^{SS}
Aggregate	-0.31 (4.13)**	-0.45 (2.43)*	-0.17 (2.42)*	0.02 (0.11)

	65:I - 79:IV		80:I - 97:II	
Cutoff in years	β^{SD}	β^{SS}	β^{SD}	β^{SS}
1	−0.71 (3.05)**	−0.91 (1.93)+	−0.68 (3.53)**	−0.51 (0.83)
2	−0.24 (1.12)	−0.21 (0.96)	−0.32 (2.49)**	0.10 (0.73)
3	−0.23 (1.28)	−0.25 (1.45)	−0.25 (1.98)+	0.15 (0.86)
4	−0.52 (2.82)**	−0.45 (2.04)*	−0.34 (4.28)**	0.16 (0.60)
5	−0.33 (2.46)*	−0.39 (2.17)*	−0.25 (2.96)**	0.21 (1.09)
6	−0.35 (2.44)*	−0.45 (2.40)*	−0.24 (4.01)**	0.19 (1.06)
7	−0.36 (2.41)*	−0.48 (2.53)*	−0.24 (5.02)**	0.15 (0.89)
8	−0.37 (2.46)*	−0.51 (2.63)**	−0.23 (7.05)**	0.09 (0.51)
9	−0.38 (2.54)*	−0.52 (2.72)**	−0.24 (10.06)**	0.05 (0.25)
10	−0.38 (2.65)**	−0.52 (2.81)**	−0.24 (19.36)**	0.01 (0.07)

Numbers in parentheses denote absolute t−values that are based on the Newey-West autocorrelation and heteroskedasticity consistent covariance matrix estimators. Superscripts +, *, and ** denote statistical significance at 10%, 5%, and 1%, respectively.

[Figure 1] Innovations in GNP Growth