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Hiroaki Miyamoto
University of Tokyo

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School of Economics and Management
Research Center for Social Design Engineering
Kochi University of Technology

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University of Tokyo

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Abstract

This paper studies the cyclicality of aggregate real wages in Japan. By using both static and dynamic approaches, I measure comovements between real wages and business cycle indicators. This paper finds that while real wages constructed using the consumer price index and the GDP deflator are procyclical, the real wage constructed using the producer price index is countercyclical. This result is robust to the data and methods used to compute the comovements.

Keywords: Real wages, business cycle, correlation

JEL Classification codes: E32, J30, C10

*Hiroaki Miyamoto. Mailing address: Graduate School of Public Policy, The University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-0033 JAPAN. Tel. +81-3–5841-1411. E-mail: miyamoto@pp.u-tokyo.ac.jp

1 Introduction

Empirical evidence about the cyclicality of aggregate real wages is inconclusive. In their survey of the literature, Abraham and Haltiwanger (1995) find that the cyclicality of real wages depends on the data and the methods used to measure comovements between real wages and business cycle indicators. While the cyclicality of real wages has been studied in the US and European countries, surprisingly there is little systematic empirical evidence for Japan.[1] This paper establishes a set of stylized facts on the cyclicality of aggregate real wages in Japan.

To understand how real wages move over the business cycle is important for identifying the sources and features of labor market dynamics. Thus, it is also of great relevance for monetary policy. Furthermore, to provide a clear picture about the cyclical behavior of real wages is now crucial in Japan. Under *Abenomics*, the Bank of Japan is now conducting aggressive quantitative easing policy to overcome deflation and achieve the price stability target of 2% inflation.[2] Since *Abenomics* has lowered real wages as prices have risen more than nominal wages, the development of real wages is receiving a great attention.

This paper measures comovement between real wages and business cycle indicators using not only a static approach but also two dynamic approaches: the time domain approach proposed by den Haan (2000) and the frequency domain approach proposed by Croux et al. (2001). Since it is known that the cyclicality of real wages is influenced by the price deflator used to compute real wages, this paper takes this into account by considering three alternative price deflators such as the consumer price index (CPI), the GDP deflator, and the producer price index (PPI).[3]

This paper finds that while real wages constructed using the CPI and GDP deflator are procyclical, the real wage constructed using the PPI is counter-cyclical. This confirms results of existing studies that examine the cyclicality of real wages in the US. I demonstrate that this result is robust to methods to measure the comovement between real wages and the business cycle.

The facts established in this study provide important implications to researchers who are interested in the Japanese labor market or in the international comparison of labor markets. Furthermore, empirical results of this paper provide a guideline of the empirical features that theoretical models should ideally have.

[1]See the survey of Abraham and Haltiwanger (1995). Messina et al. (2009) examine the cyclicality of real wages in the OECD countries by focusing on the manufacturing sectors. Recenlty, Marczak and Beissinger (2013) study the cyclicality of real wages in Germany.

[2]*Abenomics* is a policy packages consisting of aggressive monetary easing with inflation targeting; flexible fiscal policy; and growth strategy conducted by the Japanese Prime Minister Shinzo Abe after December 2012. See Hausman and Wieland (2014) and Ito (2013) for *Abenomics*.

[3]See Abraham and Haltiwanger (1995).

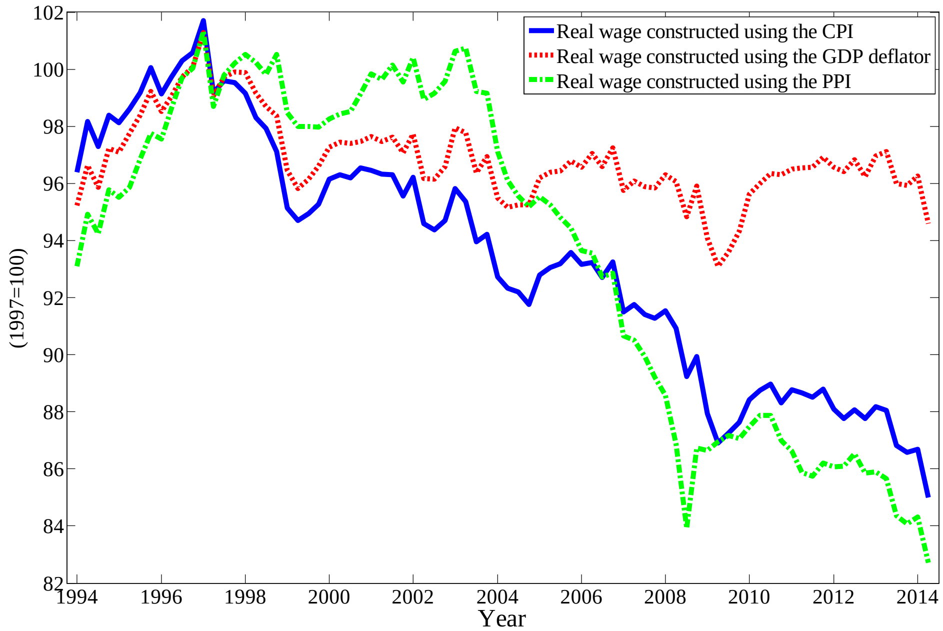

Figure 1: Real wages measures, 1994-2014

2 Data

The variables used to measure real wages are nominal wages, Consumer Price Index (CPI), Gross Domestic Product (GDP) deflator, Producer Price Index (PPI). I obtain the nominal wages from the Monthly Labour Survey (MLS) conducted by the Ministry of Health, Labour and Welfare (MHLW). The series of the CPI and the GDP deflator are constructed by the Statistics Bureau and the Director-General for Policy Planning.[4] I obtain the series of the PPI from the Bank of Japan. I derive three real wages by using the CPI deflator (w^{cpi}), the GDP deflator (w^{gdp}), and the PPI deflator (w^{ppi}). I use the unemployment rate and the real GDP as indicators of the business cycle. All series are seasonally adjusted by the using the Census Bureau's X12 ARIMA procedure and transformed by taking natural logarithm. Our data are quarterly, which, if necessary, are obtained by simple averaging of monthly data. The sample covers 1994Q1-2014Q2.

Figure 1 displays three alternative measures of real wages. During the period of 1994-97, real wages exhibited a similar behavior. However, after 1997, there are differences among three real wages. While real wages constructed using the CPI and the PPI dropped sharply, the real wage constructed using the GDP deflator has been relatively stable over time. Specifically, while the real wage constructed using the GDP deflator in 2014Q2 is about 6% lower than in 1997,

[4]Note that this study use "household consumption excluding imputed rent" as the GDP deflator.

the real wage constructed using the CPI has dropped nearly 15% in the last 17 years. This difference comes from the fact that the GDP deflator constantly shows larger rate of decline than the CPI. The discrepancy between the CPI and the GDP deflator is mainly ascribable to the different things they cover. Other causes of the discrepancy include, among others, the different calculation formulae employed.[5]

3 Empirical analysis

In this section, I examine the cyclical properties of real wages by using three alternative measures of comovements: the correlation coefficients of filtered series, the dynamic correlation proposed by Croux et al. (2001), and the correlations of VAR forecast errors at different time horizons developed by den Haan (2000).

Correlation I begin by computing correlations between real wages and a level of economic activity. I use the unemployment rate and the real GDP as indicators of the business cycle. To obtain the cyclical components of the data, I use two alternative detrending methods: the Hodrick and Prescott (HP) filter with the smoothing parameter 1600 and the Baxter-King (BK) band-pass filter. Tables 1 and 2 report correlations and relative standard deviations of each variable with business cycle indicators.

Table 1: Correlation between real wages and the unemployment rate at different leads and lags

		corr(x_t, u_{t+k})								
Filter	x_t	-4	-3	-2	-1	0	1	2	3	4
HP filter										
	w^{cpi}	0.10	-0.04	-0.20	-0.32	-0.23	-0.45	-0.46	-0.40	-0.36
	w^{gdp}	0.14	0.01	-0.14	-0.25	-0.36	-0.38	-0.38	-0.35	-0.33
	w^{ppi}	0.30	0.25	0.24	0.18	0.18	0.10	-0.07	-0.24	-0.38
BK-filter										
	w^{cpi}	0.08	-0.08	-0.25	-0.41	-0.53	-0.55	-0.50	-0.38	-0.23
	w^{gdp}	0.14	-0.02	-0.19	-0.34	-0.46	-0.48	-0.43	-0.32	-0.19
	w^{ppi}	0.34	0.36	0.36	0.21	0.23	0.12	-0.012	-0.15	-0.25

Contemporaneous correlations between real wages and the unemployment rate are negative for all detrending methods, except for the real wage constructed using the PPI. This suggests that the real wages constructed by the CPI and the GDP deflator are pro-cyclical. This finding is robust to the choice of the business cycle indicator. Contemporaneous correlations between the real wages and the real GDP are positive for all detrending methods, showing that real wages

[5] Please see the website of Statistics Bureau in Japan for the detail

Table 2: Correlation between real wages and the real GDP at different leads and lags

		corr(x_t, y_{t+k})								
Filter	x_t	-4	-3	-2	-1	0	1	2	3	4
HP filter										
	w^{cpi}	0.07	0.23	0.41	0.52	0.57	0.51	0.37	0.22	0.07
	w^{gdp}	0.06	0.20	0.35	0.46	0.53	0.49	0.35	0.19	0.03
	w^{ppi}	0.33	0.39	0.40	0.25	0.10	-0.05	-0.18	-0.22	-0.23
BK-filter										
	w^{cpi}	0.01	0.24	0.46	0.61	0.66	0.55	0.35	0.13	-0.04
	w^{gdp}	-0.04	0.21	0.44	0.58	0.61	0.48	0.28	0.08	-0.06
	w^{ppi}	-0.38	-0.36	-0.28	-0.12	0.08	0.25	0.37	0.41	0.37

are pro-cyclical. Correlations between real wage deflated by the GDP deflator and the CPI are larger than the correlation between the real wage deflated by PPI. This implies that the cyclical behavior of the real wage constructed using the PPI is somewhat different from those of the real wages constructed using the CPI and the GDP deflator. Tables 1 and 2 also report the results of cross-correlation analysis. Basically, cyclical patterns hold true at leads and lags of up to four quarters, except the real wage deflated by the PPI.

Dynamic correlation To compute the correlations between cyclical components of real wages and business cycle indicators is not the only way to study the cyclicality of real wages. We now measure comovements between real wages and the business cycle indicator by using the frequency domain approach proposed by Croux et al. (2001) and the time domain approach proposed by den Haan (2000).

These two measures have advantages over the static correlations derived from cyclical components of time series that are obtained by using the HP and the BK bandpass filters. As Messina et al. (2009) pointed out, the HP and the BK bandpass filters have some problems to extract a business cycle component of the economic time series by removing low frequency trends.[6] In contrast, the dynamic methods used in the paper overcome these disadvantages of the standard methods. Furthermore, the time domain approach proposed by den Haan (2000) accommodates both stationary and non-stationary processes and does not require identifying assumptions that are usually needed for VAR estimation.

Croux et al. (2001) develop the notion of dynamic correlation. This measure is a correlation defined with the frequency domain. Consider two zero-mean real stochastic processes x and y.

[6]The HP filter is subject to an arbitrary choice of the smoothing parameter. The BK bandpass filter is only an approximation of the ideal band-pass filter since a number of observations at the beginning and the end of the sample are lost in its computation.

Let $S_x(\omega)$ and $S_y(\omega)$ be the spectral density functions of x and y and $C_{xy}(\omega)$ be cospectrum at frequency $-\pi \leq \omega \leq \pi$. Then, the dynamic correlation between x and y is given by

$$\rho_{xy}(\omega) = \frac{C_{xy}(\omega)}{\sqrt{S_x(\omega)S_y(\omega)}}$$

for $0 \leq \omega \leq \pi$. This measure is a real number that takes values between -1 and 1. I can also compute the correlation between two series on a frequency band. Let Λ be a frequency band which satisfies the following definition: $\Lambda = \Lambda_+ \cup \Lambda_-$, where $\Lambda_+ = [\omega_1, \omega_2)$ and $\Lambda_- = [-\omega_2, -\omega_1)$ and $0 \leq \omega_1 \leq \omega_2 \leq \pi$. Then, the static correlation coefficient between x_t and y_t over the frequency band Λ_+ is defined by

$$\rho_{xy}(\Lambda_+) = \frac{\int_{\Lambda_+} C_{xy}(\omega)d\omega}{\sqrt{\int_{\Lambda_+} S_x(\omega)d\omega \int_{\Lambda_+} S_y(\omega)dw}} = \frac{\int_{\Lambda_+} \rho_{xy}(\omega)\sqrt{S_x(\omega)S_y(\omega)}d\omega}{\sqrt{\int_{\Lambda_+} S_x(\omega)d\omega \int_{\Lambda_+} S_y(\omega)dw}}.$$

Following Baxter and King (1999) and Stock and Watson (1999), I divide the frequency interval $[0, \pi]$ into three bands: the low-frequency band, the medium frequency band, and the high frequency band. These three frequency bands correspond to the long-run, the business cycle and the irregular, respectively. In practice, I use a standard decomposition of the frequency band. Thus, the low-frequency band is $[0, \pi/16]$ (i.e., cycles of 8 years of longer), the medium-frequency band is $[\pi/16, \pi/3]$ (i.e., cycles of 1.5-8 years), and the high-frequency band is $[\pi/3, \pi]$ (i.e., cycles of 1.5 years or less).

Table 3: Correlation coefficient between real wages and the unemployment rate over the frequency bands

	Frequency bands Λ_+			
	All	Long-run	Business cycle	Irregular
w^{cpi}	-0.39	-0.42	-0.38	-0.26
w^{gdp}	-0.38	-0.48	-0.35	-0.13
w^{ppi}	0.00	-0.04	0.02	0.09

Figure 2 depicts the dynamic correlations between real wages and the unemployment rate. The dynamic correlations for real wages constructed using the CPI and the GDP deflator show a similar pattern. The values of them are always negative over the frequency band $[\pi/16, \pi/3]$. This implies that the real wages and the unemployment rate comove negatively over the business cycle. In contrast, the dynamic correlation between the real wage constructed using the PPI and the unemployment rate shows that they comove positively over the business cycle.

Table 3 reports the static correlation coefficients over frequency bands. The static correlation coefficients of real wages constructed using the CPI and the GDP deflator are negative for both

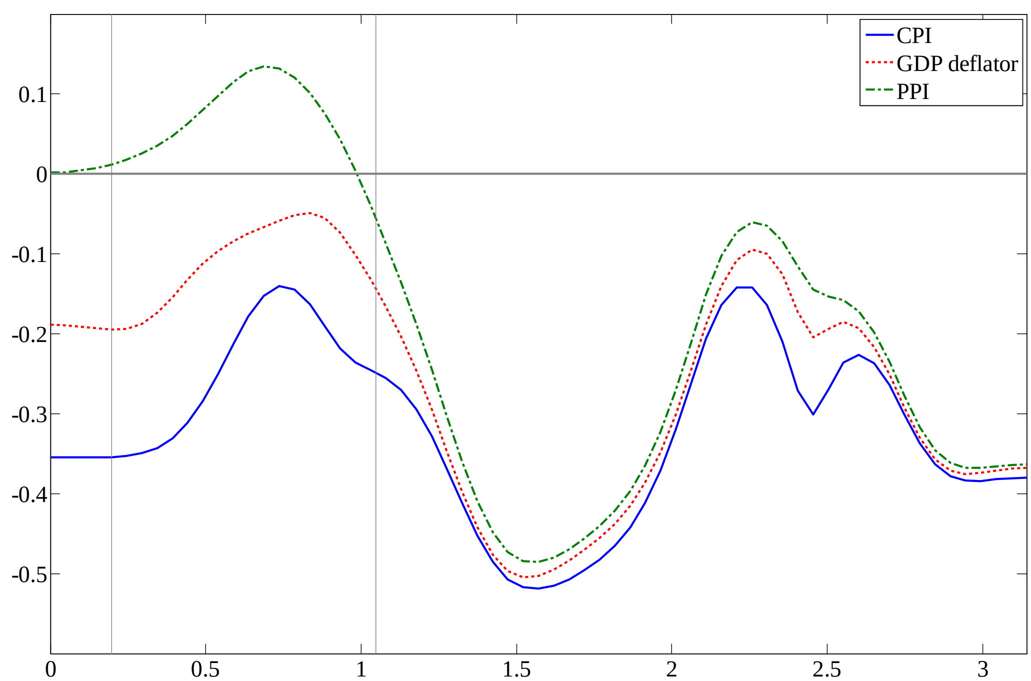

Figure 2: Dynamic correlation between real wages and the unemployment rate
Note: The solid line labeled "CPI" plots the dynamic correlation for the real wage constructed using the CPI. The dashed line labeled "GDP deflator" plots the dynamic correlation for the real wage constructed using the GDP deflator. The dash-dotted line labeled "PPI" plots the dynamic correlation for the real wage constructed using the PPI.

long-run and business cycle movements, while those for the real wage constructed using the PPI are positive.

Measuring comovement with VAR forecast errors den Haan (2000) proposes an alternative measure of comovement which uses the correlations of VAR forecast errors at different horizons. Consider X_t, the 2×1 vector containing the log of the unemployment rate, u_t, and the log of a real wage measure, w_t. The vector X_t is allowed to contain any combination of stationary processes and processes that are integrated of arbitrary order. Following den Haan (2000), this paper calculates correlation coefficients of forecast errors at different forecast horizons, obtained from the estimation of various specification of the following VAR model:

$$X_t = \alpha_0 + \alpha_1 t + \alpha_2 t^2 + \sum_{l=1}^{L} A_l X_{t-l} + \varepsilon_t,$$

where the A_t is 2×2 matrix of regression coefficients, α_0, α_1, and α_3 are 2×1 vectors of coefficients, ε_t is a 2×1 vector of innovations that are assumed to be serially uncorrelated but can be correlated with each other, and the total number of lags included is equal to L. The K-period ahead forecast errors of the variables u_t and w_t are denoted by $u^{ue}_{t+K,t}$ and $w^{ue}_{t+K,t}$, respectively. The covariance and the correlation coefficient between these two variables is denoted by $COV(K)$ and $COR(K)$, respectively. If the series are stationary, then the correlation coefficient of the forecast errors will converge to the unconditional correlation coefficient of the two series as the forecast horizon K goes to infinity. In the case some of the time series are not stationary, statistics then might not converge but $COV(K)$ and $COR(K)$ can still be estimated consistently for fixed K. Given estimates of the regression coefficients and the covariance matrix of ε_t, it is relatively straightforward to calculate the implied covariance and correlation coefficient between the K-period ahead forecast errors of the unemployment rate and the real wage measure

Applying this methodology, I estimate 3 bivariate VAR models. The characteristics of the estimated VAR models are summarized in Table 4. Akaike information criterion is used to determine the number of lags and whether linear and quadratic trend terms should be included.

Table 4: Characteristics of the estimated bivariate VAR

Variable	Unit root	Number of lags	Linear trend	Quadratic trend
w^{cpi}	Yes	1	No	No
w^{gdp}	Yes	1	Yes	No
w^{ppi}	Yes	6	No	No

Figure 3 plots the correlation coefficients based on VAR forecast errors along with their 90 percent confidence intervals. For the model with real wages constructed using the CPI and the GDP deflator, the coefficients are significantly negative at all horizons. This confirms the results from the frequency domain analysis. In contrast, although they are not statistically significant, the coefficients are positive at all horizons when I use the real wage constructed using the PPI.

To summarize, the cyclicality of the real wages in Japan differs according to the data used to measure the real wages. This study finds that the real wages are procyclical when the CPI and the GDP deflator are used to deflate the nominal wage series, but that they are countercyclical when the PPI is used to deflate. This finding is robust to methods to compute comovements between real wages and business cycle indicators.

4 Conclusion

While the cyclicality of aggregate real wages has been studied in the U.S. and European countries, little is known about a cyclical behavior of aggregate real wages in Japan. This paper tries to fill this gap and provide a stylized fact of the real wage dynamics over the business cycle in Japan. By using both static and dynamic approaches, I compute comovements between real wages and business cycle indicators. This paper finds that while real wages constructed using the CPI and the GDP deflator are procyclical, the real wage constructed using the PPI is countercyclical. The stylized facts established in the paper are of interest policy makers and macroeconomists. For policy makers, they can help identify the features of labor market dynamics that is of great relevance for monetary policy. For macroeconomists, they provide a guideline of the empirical features that theoretical models should ideally have.

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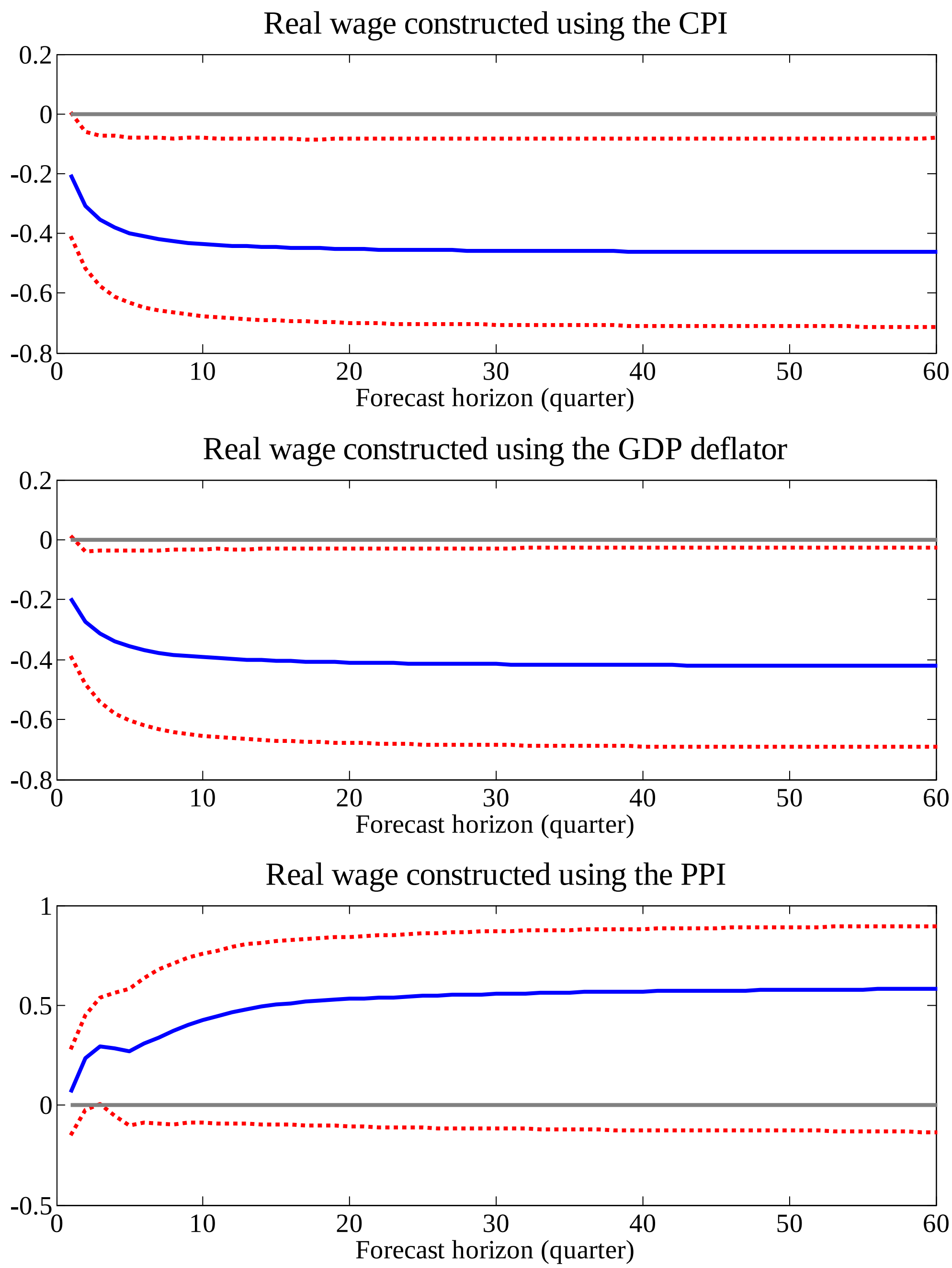

Figure 3: Comovement between real wages and the unemployment rate
Note: Solid lines are the correlation coefficients of the *K*-period ahead forecast errors of the real wages and the unemployment rate. Dashed lines indicate the 90 percent confidence bands, constructed by the bootstrap method.

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