Causal relationship between wages and prices in UK: VECM analysis and Granger causality testing

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Abstract

In this paper the issue of causality between wages and prices in UK has been tested. OLS relationship between prices and wages is positive; productivity is not significant in determination of prices or wages too. These variables from these statistics we can see that are stationary at 1 lag, i.e. they are I(1) variables, except for CPI variables which is I(2) variable. From the VECM model, if the log wages increases by 1%, it is expected that the log of prices would increase by 5.24 percent. In other words, a 1 percent increase in the wages would induce a 5.24 percent increase in the prices. About the short run parameters, the estimators of parameters associated with lagged differences of variables may be interpreted in the usual way. Productivity was exogenous repressor and it is deleted since it has coefficient no different than zero. The relation (causation) between these two variables is from CPI_log→real_wage_log. Granger causality test showed that only real wages influence CPI or consumer price index that proxies prices, this is one way relationship, price do not influence wages in our model.

Keywords: VECM, Granger causality, real wages, prices, cointegration, OLS
Introduction

In the literature from this area there two sides of economist one that thinks that causality runs from wages to prices and the second that thinks that causality runs from wages to prizes. The evidence in the literature has evidence in support to both hypotheses. Granger causality test is easy to be applied in economics. OLS techniques have been applied to data, and to estimate the long run relationship we apply VECM analysis.

Theoretical overview

In this theoretical review some basic concepts in the theory of wages and prices are outlined, to explain in some extent: what are determinants of wages and prices from neo-classical and neo-keynesian perspective.

The Issue of Time Consistency

New Classical Analysis makes a distinction between anticipated and unanticipated changes in money supply. There exists superiority of fixed policy rules, low inflation requires monetary authorities to commit themselves to low-inflation policy. Government cannot credibly commit to low inflation policy if retain the right to conduct discretionary policy (Kydland, Prescott, 1977). The model of optimal policy is as follows:

Let $\pi = (\pi_1, \pi_2, \ldots, \pi_T)$ be a sequence of policies for periods 1 to $T$ and $x = (x_1, x_2, \ldots, x_T)$ be the corresponding sequence of economic agents’ decisions.

Assume an agreed social welfare function:

$$S (x_1, x_2, \ldots, x_T, \pi_1, \pi_2, \ldots, \pi_T)$$  \hspace{1cm} (1)

And that agents’ decisions in period $t$ depend on all policy decisions and their own past decisions:

$$x_t = X_t (x_1, x_2, \ldots, x_{t-1}, \pi_1, \pi_2, \ldots, \pi_T) \hspace{1cm} (2)$$

An optimal policy is one which maximises (1) subject to (2). The issue of time consistency is:

A policy $\pi$ is time consistent if for each $t$, $\pi_t$ maximises (1) taking as given previous economic agents’ decisions and that future policy decisions are taken similarly. Optimal policies are time inconsistent

- therefore lack credibility
- discretionary policies lead to inferior outcomes
– need credible pre-commitment

Consider a two period model in which \( \pi_2 \) is selected to maximise:

\[
S (x_1, x_2, \pi_1, \pi_2) \tag{3}
\]

subject to:

\[
x_1 = X_1 (\pi_1, \pi_2) \quad \text{and} \quad x_2 = X_2 (x_1, \pi_1, \pi_2) \tag{4}
\]

For the policy to be time consistent \( \pi_2 \) must maximise (3), given \( x_1 \) and \( \pi_1 \) and given constraint (4). Now we are going to eliminate inflatory bias:

Low inflation rule not credible if government retains discretionary powers

• need to gain a reputation for maintaining a low inflation policy mix
  – benefits from cheating < punishment costs
• or need to pre-commit to a low inflation policy goal
  – central bank independence, ‘golden rule’ for fiscal policy
  – but danger of democratic deficit?

Sources of price rigidity

New Keynesians suggest that small nominal price rigidities may have large macro effects

– incomplete indexing of prices in imperfectly competitive goods, labour and financial markets may be costly in terms of output instability

In goods market small ‘menu costs’ + unsynchronised price adjustments lead to staggered price adjustments

– fear that rapid price adjustments costly in decision-making time and cause excessive loss of existing customers

Sources of wage rigidity

Efficiency wages

Economy of high wages – productivity and non-wage labour costs may be endogenous in the wage-fixing process, even given excess supply of labour firms may not lower wages because their unit labour costs may rise \( \rightarrow \) persistent unemployment. This repeals law of supply and demand, if the relationship between wages and productivity/non-wage costs varies across industry repeals law of one price. Version of efficiency wage model is:

A representative firm seeks to maximise its profits:

\[
\pi = Y - wL \tag{1}
\]

where \( Y \) firm’s output and \( wL \) its wage costs and:
\[ Y = F(eL) \quad F' > 0, \quad F'' < 0 \] (2)

where \( e \) is workers’ effort and:

\[ e = e(w) \quad e' > 0 \] (3)

there are \( L^0 \) identical workers who each supply 1 unit of labour inelastically

The problem of the firm is to:

\[ \max_{L,w} F(e(w)L) - wL \] (4)

when there is unemployment the first order conditions for \( L \) and \( w \) are:

\[ F'(e(w)L)e(w) - w = 0 \] (5)

\[ F'(e(w)L)L e'(w) - L = 0 \] (6)

rewriting (5) gives:

\[ F'(e(w)L) = w / e(w) \] (7)

substituting (7) into (5) gives:

\[ we'(w) / e(w) = 1 \] (8)

From (8) at the optimum, the elasticity of effort with respect to wage is 1, i.e. the efficiency wage (\( w^* \)) is that which satisfies (8) and minimises the cost of effective labour

With \( N \) firms each hiring \( L^* \) (the solution to (7), then total employment is \( NL^* \) and as long as \( NL^* < L^+ \) we observe an efficiency wage (\( w^* \)) and unemployment

\section*{Literature overview}

Empirical facts on the price, wage and productivity relationship - The debate on the direction of causality between wages and prices is one of the central questions surrounding the literature on the determinants of inflation. The purpose of this review is to identify the key theories, concepts or ideas explaining the causality issue between prices and wages. We selected ten studies as to see what method they use in explanation of this relationship, most of the studies use panel methods but some use VECM model just like ours too.
A summary of some studies on the price, wage and productivity relationship

<table>
<thead>
<tr>
<th>Studies</th>
<th>Title</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Saten Kumar, Don J. Webber and Geoff Perry (2008)</td>
<td>Real wages, inflation and labour productivity in Australia</td>
<td>Cointegration; Granger causality</td>
</tr>
<tr>
<td>Dubravko Mihaljev and Sweta Saxena</td>
<td>Wages, productivity and “structural” inflation in emerging market economies</td>
<td>Empirical methods, correlations</td>
</tr>
<tr>
<td>Erica L. Groshen Mark E. Schweitzer (1997)</td>
<td>The Effects of Inflation on Wage Adjustments in Firm-Level Data: Grease or Sand?</td>
<td>40-year panel of wage changes</td>
</tr>
<tr>
<td>Kawasaki, Hoeller, Poret, 1997</td>
<td>Modeling wages and prices for smaller OECD countries</td>
<td>Error correction mechanism</td>
</tr>
<tr>
<td>SHIK HEO (2003)</td>
<td>THE RELATIONSHIP BETWEEN EFFICIENCY WAGES AND PRICE INDEXATION IN A NOMINAL WAGE CONTRACTING MODEL</td>
<td>simple nominal wage contracting model</td>
</tr>
<tr>
<td>John B. Taylor (1998)</td>
<td>STAGGERED PRICE AND WAGE SETTING IN MACROECONOMICS</td>
<td>time-dependent pricing, staggered price and wage setting</td>
</tr>
<tr>
<td>Gregory D. Hess and Mark E. Schweitzer</td>
<td>Does Wage Inflation Cause Price Inflation?</td>
<td>Granger Causality, panel econometrics</td>
</tr>
<tr>
<td>Raymond Robertson (2001)</td>
<td>Relative Prices and Wage Inequality: Evidence from Mexico</td>
<td>Ordered Logit, Ordered Probit</td>
</tr>
</tbody>
</table>

This table shows that there exist theoretical and empirical models for prices and wages. This is a small sample of ten studies that study the relationship between wages, prices and productivity.
**Data and the methodology**

We use time series data here for UK industry. Three variables are selected for the model. **LRW** is the log of real wage. This variable represents Real Hourly Compensation in Manufacturing, CPI Basis, in the United Kingdom. The data are from 1960 to 2009 although in our regressions we use data only from 1960 to 2007, because from 2008 financial crisis started which in terms of econometrics represents a huge structural break. This variable is indexed and as base is chosen 2002=100. Second variable is **LCPI** which represents logarithm of consumer price index in UK for all items from 1960 to 2009, we use 1960-2007, and it is indexed 2005=100. **LPROD** is logarithm of productivity for UK manufacturing industry, this variable was calculated on a basis of average working hours in manufacturing industry and total output of manufactured goods, second variable was divided by first, and then logarithms were put. OLS and time series methods like VECM and co-integration are going to be applied for this series of data.

**OLS regressions**

I model: Price as a function of wages and productivity

\[ CPI = f(RW, PRODUCTIVITY) \]

II model: Wage is function of price and productivity.

\[ RW = f(CPI, PRODUCTIVITY) \]

This functional form is being applied on our data.

Ordinary least squares regressions are presented in the next page\(^1\):

\(^1\) For detailed output see Appendix 1 OLS regressions
<table>
<thead>
<tr>
<th>Variables</th>
<th>$CPI = f(RW, PRODUCTIVITY)$</th>
<th>$RW = f(CPI, PRODUCTIVITY)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>log</td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>LRW</td>
<td>0.42**</td>
<td></td>
</tr>
<tr>
<td>LPROD</td>
<td>-0.017</td>
<td></td>
</tr>
<tr>
<td>CONST</td>
<td>5.81***</td>
<td></td>
</tr>
<tr>
<td>AC test</td>
<td>0.001***</td>
<td></td>
</tr>
<tr>
<td>Ramsey test</td>
<td>0.019</td>
<td></td>
</tr>
<tr>
<td>log</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>LCPI</td>
<td></td>
<td>0.21**</td>
</tr>
<tr>
<td>LPROD</td>
<td></td>
<td>0.06</td>
</tr>
<tr>
<td>CONST</td>
<td></td>
<td>3.33**</td>
</tr>
<tr>
<td>AC test</td>
<td></td>
<td>0.794**</td>
</tr>
<tr>
<td>Ramsey test</td>
<td></td>
<td>0.178**</td>
</tr>
<tr>
<td>Δlog</td>
<td>(5)</td>
<td></td>
</tr>
<tr>
<td>ΔLRW</td>
<td>0.15</td>
<td>ΔLCPI</td>
</tr>
<tr>
<td>ΔLPROD</td>
<td>-0.0051</td>
<td>0.17</td>
</tr>
<tr>
<td>CONST</td>
<td>0.053</td>
<td>ΔLPROD</td>
</tr>
<tr>
<td>AC test</td>
<td>0.000</td>
<td>CONST</td>
</tr>
<tr>
<td>Ramsey test</td>
<td>0.943**</td>
<td>AC test</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Ramsey test</td>
</tr>
<tr>
<td></td>
<td></td>
<td>0.943**</td>
</tr>
</tbody>
</table>

**Note 1:** *** - significant at 1% level of significance; ** - significant at 5% level of significance; * - significant at 10% level of significance. The AC tests indicate the p-value of the Breusch-Godfrey LM test for autocorrelation with $H_0$: no serial correlation and $H_a$: $H_0$ is not true.

Here OLS relationship between prices and wages is positive, also and between productivity and prices and productivity and wages except for the fact that these relationships are not significant. These models in column 1 can be represented in a form:

\[^\text{lcpi} = \beta_0 \text{lrw} + \beta_1 \text{prod} + \beta_0,\]

where $\beta_0$ is intercept, $\beta_1$ and $\beta_2$ are elasticities that measure elasticity of wages to prices and productivity to prices respectively. Second model in this column is: $\Delta \text{lcpi} = \beta_1 \Delta \text{lrw} + \beta_2 \Delta \text{prod} + \beta_0$, this is the case of first differences of the variables.

Autocorrelation in the models from column I is a serious problem, OLS time series do suffer from serial correlation. Functional form significant at all conventional levels of significance. Finally the estimated coefficients on wages to prices (and vice versa) are positive. This notion is not confirmed with Granger causality test, except for the case that Log of real wages causes LCPI at 5% level of significance.²

² See Appendix 2 Granger causality test
### Log-levels vs. First-differences

<table>
<thead>
<tr>
<th>NON-CAUSAL VARIABLES</th>
<th>Log-levels</th>
<th>First-differences</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LR stat</td>
<td>LR stat</td>
</tr>
<tr>
<td>LCPI</td>
<td>0.316</td>
<td>0.801</td>
</tr>
<tr>
<td>LRW</td>
<td>0.049***</td>
<td>0.133</td>
</tr>
</tbody>
</table>

**Note 1:** *** - significant at 1% level of significance; ** - significant at 5% level of significance; * - significant at 10% level of significance.

### Impulse response graph

On the next graph is given impulse Response for a shock of variables, prices and wages.

![Impulse response graph](image)

### Unit root tests

Unit root tests statistics are given in a Table below

<table>
<thead>
<tr>
<th>Variables tested for unit roots</th>
<th>Test statistic</th>
<th>Decision</th>
</tr>
</thead>
<tbody>
<tr>
<td>real_wage_log</td>
<td>-1.4627</td>
<td>Series is non-stationary</td>
</tr>
<tr>
<td>real_wage_log_d1</td>
<td>-3.5693**</td>
<td>Series is stationary</td>
</tr>
<tr>
<td>CPI_log</td>
<td>-1.1164</td>
<td>Series is non-stationary</td>
</tr>
<tr>
<td>CPI_log_d1</td>
<td>-2.3459</td>
<td>Series is non-stationary</td>
</tr>
<tr>
<td>CPI_log_d1_d1_d1</td>
<td>-7.0234***</td>
<td>Series is stationary</td>
</tr>
</tbody>
</table>

Critical values for the test at

<table>
<thead>
<tr>
<th></th>
<th>1%</th>
<th>5%</th>
<th>10%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test statistic</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-3.96</td>
<td>-3.41</td>
<td>-3.13</td>
<td></td>
</tr>
</tbody>
</table>

**Note 1:** *** - significant at 1% level of significance; ** - significant at 5% level of significance; * - significant at 10% level of significance.

---

3 See Appendix 3 Unit root tests
These variables from these statistics we can see that are stationary at 1 lag, i.e. they are I(1) variables, except for CPI variables which is I(2) variable. These variables are graphically presented as non-stationary and their differences as stationary in the unit root section Appendix 3.

**Johansen Trace test (co-integration test)**

Whereas the Akaike Information Criterion (AIC) tends to overestimate the optimal lag order, the Hannan–Quinn information criterion (HQ) provides the most consistent estimates, thus it will be considered as the most reliable criterion.

**Cointegration rank**

On the next table is summarized the decision for with how many lags to continue testing.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Deterministic trend</th>
<th>Johansen trace test</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPI_log</td>
<td>Constant</td>
<td>Lag order LR-stat p-value</td>
</tr>
<tr>
<td>and Real_wage_log</td>
<td>Constant and a trend</td>
<td>1 2.65 0.6540</td>
</tr>
</tbody>
</table>

We reject the null for zero lags and we cannot reject the r=1, so we will accept 1 cointegrating vector.

**Estimated cointegrating vector**

Next we are going to present the estimation for cointegrating vector. This estimation does not include intercepts and does not include trends.

---

4 See Appendix 4 test for cointegration
Chosen order =1
44 observations from 1964 to 2007
Vector 1
LRW  .24600  
(  -1.0000)  
LCPI  -.18411  
(  .74839)

List of variables included in the cointegrating vector:
LRW    LCPI

These vectors are normalized in brackets.

**Estimated long run coefficient using ARDL approach**

Long run coefficient between logarithm of real wages and logarithm of prizes is positive and statistically significant.

<table>
<thead>
<tr>
<th>Estimated Long Run Coefficients using the ARDL Approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARDL(1,0) selected based on Schwarz Bayesian Criterion</td>
</tr>
<tr>
<td>Dependent variable is LRW</td>
</tr>
<tr>
<td>44 observations used for estimation from 1964 to 2007</td>
</tr>
<tr>
<td>Regressor     Coefficient  Standard Error  T-Ratio[Prob]</td>
</tr>
<tr>
<td>LCPI          .74158      .030294       24.4796[.000]</td>
</tr>
</tbody>
</table>

**VECM model**

VECM model is presented in the matrix form below

Coefficient matrix
\[
\begin{bmatrix}
   d(CPI \_ log(t)) \\
   d(real \_ wage \_ log)(t)
\end{bmatrix} =
\begin{bmatrix}
   -0.105 & 1.000 & -5.246 & CPI(\log(t-1)) \\
   -0.031 & -0.010 & real \_ wage \_ log(t-1) & + [15.325] \ [CONST]
\end{bmatrix} +
\begin{bmatrix}
   TRENDS(t) \\
   u1(t) \\
   u2(t)
\end{bmatrix}
\]

VECM output consists of coefficients. **Estimation** - The VECM model was estimated using the Two Stage procedure (S2S), with Johansen procedure being used in the first stage and Feasible Generalized Least Squares (FGLS) procedure being used in the second stage. The
**Loading coefficients**—even though they may be considered as arbitrary to some extent due to the fact that they are determined by normalization of co-integrating vectors, their t ratios may be interpreted in the usual way as being conditional on the estimated co-integration coefficients, (Lütkepohl and Krätzig, 2004; Lütkepohl and Krätzig, 2005,). In our case loading coefficients have t-ratios [-12.616] [-3.907] respectively. Thus, based on the presented evidence, it can be argued that co-integration relation resulting from normalization of cointegrating vector enters significantly. Table of t-stat matrix is given below.

t-stat matrix

\[
\begin{bmatrix}
  d(CPI_{t\log}) \\
  d(real \_wage \_log(t))
\end{bmatrix} = 
\begin{bmatrix}
  -12.616 \\
  -3.907
\end{bmatrix} + 
\begin{bmatrix}
  CPI(t-1) \\
  real \_wage(t-1)
\end{bmatrix} + 
\begin{bmatrix}
  8.779
\end{bmatrix} + 
\begin{bmatrix}
  u1(t) \\
  u2(t)
\end{bmatrix}
\]

**Co-integration vectors** — The model we can arrange as follows

\[
ec_{fgls} = CPI_{t\log} - 5.246 real \_wage \_log
\]

(-10.401)

If we rearrange

\[
CPI_{t\log} = 5.246 real \_wage \_log + ec_{fgls}
\]

(-10.401)

If the log wages increases by 1%, it is expected that the log of prices would increase by 5.24 percent. In other words, a 1 percent increase in the log wages would induce a 5.24 percent increase in the log of prices.

**Short-run parameters** - The estimators of parameters associated with lagged differences of variables may be interpreted in the usual way. Productivity was exogenous regressor and it is deleted since it has coefficient no different than zero.
**Deterministic Terms** – Trend term has statistically significant though very small impact in the two equations.

**Conclusion**

In our paper we made several conclusions about the relationship between prices and wages. First there exist positive and significant relationship between the two variables and causation is from real wages to CPI. As our Vector Error correction model (VECM) showed on average 1% increase in log of real wages induces by 5.3% increase in CPI for all items in UK, i.e. this means that increase in wages causes inflation in UK, this notion was confirmed with the Granger causality test. The relation (causation) between these two variables is from CPI_log $\rightarrow$ real_wage_log.
Appendix 1 OLS regressions

Ordinary Least Squares Estimation

Dependent variable is LRW

<table>
<thead>
<tr>
<th>Regressor</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-Ratio [Prob]</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>3.3245</td>
<td>1.0646</td>
<td>3.1228 [.003]</td>
</tr>
<tr>
<td>LCPI</td>
<td>.20940</td>
<td>.10131</td>
<td>2.0670 [.045]</td>
</tr>
<tr>
<td>LPROD</td>
<td>.055376</td>
<td>.036035</td>
<td>1.5367 [.131]</td>
</tr>
</tbody>
</table>

R-Squared: .13049  
S.E. of Regression: .87654  
F-statistic: F(  2,  45) 3.3766 [.043]

Mean of Dependent Variable: 6.0656  
S.D. of Dependent Variable: .91980

Residual Sum of Squares: 34.57
Equation Log-likelihood: -60.2352
Akaike Info. Criterion: -63.2352  
Schwarz Bayesian Criterion: -66.0420

Diagnostic Tests

<table>
<thead>
<tr>
<th>Test Statistics</th>
<th>LM Version</th>
<th>F Version</th>
</tr>
</thead>
<tbody>
<tr>
<td>A:Serial Correlation*</td>
<td>CHSQ( 1)= .068405 [.794]*</td>
<td>F( 1,  44)= .062794 [.803]*</td>
</tr>
<tr>
<td>B:Functional Form</td>
<td>CHSQ( 1)= 1.8114 [.178]*</td>
<td>F( 1,  44)= 1.7256 [.196]*</td>
</tr>
<tr>
<td>C:Normality</td>
<td>CHSQ( 2)= 21.5106 [.000]*</td>
<td>Not applicable</td>
</tr>
<tr>
<td>D:Heteroscedasticity</td>
<td>CHSQ( 1)= .066142 [.797]*</td>
<td>F( 1,  46)= .063473 [.802]*</td>
</tr>
<tr>
<td>E:Predictive Failure</td>
<td>CHSQ( 2)= .72414 [.696]*</td>
<td>F( 2,  45)= .36207 [.698]*</td>
</tr>
</tbody>
</table>

A: Lagrange multiplier test of residual serial correlation
B: Ramsey’s RESET test using the square of the fitted values
C: Based on a test of skewness and kurtosis of residuals
D: Based on the regression of squared residuals on squared fitted values
E: A test of adequacy of predictions (Chow’s second test)

Test for autocorrelation

Test of Serial Correlation of Residuals (OLS case)

Dependent variable is LRW

List of variables in OLS regression:
C  
CPI  
LPROD

48 observations used for estimation from 1960 to 2007

<table>
<thead>
<tr>
<th>Regressor</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-Ratio [Prob]</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS RES(-1)</td>
<td>-0.038067</td>
<td>.15191</td>
<td>-.25059 [.803]</td>
</tr>
</tbody>
</table>

Lagrange Multiplier Statistic  
CHSQ( 1)= .068405 [.794]
F Statistic  
F( 1,  44)= .062794 [.803]
Ordinary Least Squares Estimation

Dependent variable is LCPI
48 observations used for estimation from 1960 to 2007

<table>
<thead>
<tr>
<th>Regressor</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-Ratio[Prob]</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>5.8088</td>
<td>1.4061</td>
<td>4.1311[.000]</td>
</tr>
<tr>
<td>LRW</td>
<td>.41409</td>
<td>.20033</td>
<td>2.0670[.045]</td>
</tr>
<tr>
<td>LPROD</td>
<td>-.016950</td>
<td>.051925</td>
<td>-.32643[.746]</td>
</tr>
</tbody>
</table>

R-Squared                    .087020   R-Bar-Squared                  .046443
S.E. of Regression           1.2326   F-stat. F(  2,  45)             2.1446[.129]
Mean of Dependent Variable   7.9939   S.D. of Dependent Variable     1.2623
Residual Sum of Squares      68.3711   Equation Log-likelihood       -76.5990
Akaike Info. Criterion       -79.5990  Schwarz Bayesian Criterion    -82.4058
DW-statistic                 .99136

Diagnostic Tests

Test for autocorrelation

Test of Serial Correlation of Residuals (OLS case)

Dependent variable is LCPI
48 observations used for estimation from 1960 to 2007

<table>
<thead>
<tr>
<th>Regressor</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-Ratio[Prob]</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS RES(- 1)</td>
<td>.51226</td>
<td>.13395</td>
<td>3.8244[.000]</td>
</tr>
</tbody>
</table>

Lagrange Multiplier Statistic CHSQ( 1)= 11.9751[.001]
F Statistic F(  1,  44)= 14.6262[.000]
Ordinary Least Squares Estimation

Dependent variable is DLRW
47 observations used for estimation from 1961 to 2007

<table>
<thead>
<tr>
<th>Regressor</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-Ratio[Prob]</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.016183</td>
<td>0.18532</td>
<td>0.087324[.931]</td>
</tr>
<tr>
<td>DLCPI</td>
<td>0.16411</td>
<td>0.15873</td>
<td>1.0340[.307]</td>
</tr>
<tr>
<td>DLPROD</td>
<td>0.037112</td>
<td>0.035729</td>
<td>1.0387[.305]</td>
</tr>
</tbody>
</table>

R-Squared        .046583   R-Bar-Squared        .0032454
S.E. of Regression 1.2690   F-stat. F( 2, 44) 1.0749[.350]
Mean of Dependent Variable .026783   S.D. of Dependent Variable 1.2711
Residual Sum of Squares 70.8578   Equation Log-likelihood -76.3375
Akaike Info. Criterion -79.3375   Schwarz Bayesian Criterion -82.1127
DW-statistic        2.9188

Diagnostic Tests

* Test Statistics * LM Version * F Version *

* A:Serial Correlation*CHSQ(1)= 10.4302[.001]*F(1, 43)= 12.2642[.001]*
* B:Functional Form *CHSQ(1)= .86120[.353]*F(1, 43)= .80261[.375]*
* C:Normality *CHSQ(2)= .16722[.920]* Not applicable *
* D:Heteroscedasticity*CHSQ(1)= .39955[.527]*F(1, 45)= .38583[.538]*
* E:Predictive Failure*CHSQ(2)= .0011216[1.00]*F(2, 44)= .5608E-3[1.00]*

A: Lagrange multiplier test of residual serial correlation
B: Ramsey's RESET test using the square of the fitted values
C: Based on a test of skewness and kurtosis of residuals
D: Based on the regression of squared residuals on squared fitted values
E: A test of adequacy of predictions (Chow's second test)

Test for autocorrelation
Test of Serial Correlation of Residuals (OLS case)

Dependent variable is DLRW
List of variables in OLS regression:
C  DLCPI  DLPROD
47 observations used for estimation from 1961 to 2007

<table>
<thead>
<tr>
<th>Regressor</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-Ratio[Prob]</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS RES(−1)</td>
<td>-.48305</td>
<td>.13793</td>
<td>-3.5020[.001]</td>
</tr>
</tbody>
</table>

Lagrange Multiplier Statistic CHSQ(1)= 10.4302[.001]
F Statistic F(1, 43)= 12.2642[.001]
Ordinary Least Squares Estimation

Dependent variable is DLCPI
47 observations used for estimation from 1961 to 2007

<table>
<thead>
<tr>
<th>Regressor</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-Ratio [Prob]</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>.052526</td>
<td>.17375</td>
<td>.30230 [.764]</td>
</tr>
<tr>
<td>DLRW</td>
<td>.14454</td>
<td>.13979</td>
<td>1.0340 [.307]</td>
</tr>
<tr>
<td>DLPROD</td>
<td>-.0051790</td>
<td>.033930</td>
<td>-.15264 [.879]</td>
</tr>
</tbody>
</table>

R-Squared: .023721   R-Bar-Squared: .020655
S.E. of Regression: 1.1909   F-stat: F(  2,  44) = 18.5274 [.000]
Mean of Dependent Variable: .056205   S.D. of Dependent Variable: 1.1788
Residual Sum of Squares: 62.4047   Equation Log-likelihood: -73.3522
Akaike Info. Criterion: -76.3522   Schwarz Bayesian Criterion: -79.1274
DW-statistic: 3.0912

Diagnostic Tests

<table>
<thead>
<tr>
<th>Test Statistics</th>
<th>LM Version</th>
<th>F Version</th>
</tr>
</thead>
<tbody>
<tr>
<td>A: Serial Correlation</td>
<td>CHSQ( 1)= 14.1529 [.000]</td>
<td>F( 1, 43)= 18.5274 [.000]</td>
</tr>
<tr>
<td>B: Functional Form</td>
<td>CHSQ( 1)= .0050795 [.943]</td>
<td>F( 1, 43)= .0046477 [.946]</td>
</tr>
<tr>
<td>C: Normality</td>
<td>CHSQ( 2)= 156.5101 [.000]</td>
<td>Not applicable</td>
</tr>
<tr>
<td>D: Heteroscedasticity</td>
<td>CHSQ( 1)= .37556 [.540]</td>
<td>F( 1, 45)= .36248 [.550]</td>
</tr>
<tr>
<td>E: Predictive Failure</td>
<td>CHSQ( 2)= .0010102 [.00]</td>
<td>F( 2, 44)= .5051E-3 [.00]</td>
</tr>
</tbody>
</table>

Test of Serial Correlation of Residuals (OLS case)

Dependent variable is DLCPI
List of variables in OLS regression:
C               DLRW            DLPROD
47 observations used for estimation from 1961 to 2007

<table>
<thead>
<tr>
<th>Regressor</th>
<th>Coefficient</th>
<th>Standard Error</th>
<th>T-Ratio [Prob]</th>
</tr>
</thead>
<tbody>
<tr>
<td>OLS RES(- 1)</td>
<td>-.55190</td>
<td>.12822</td>
<td>-4.3043 [.000]</td>
</tr>
</tbody>
</table>

Lagrange Multiplier Statistic: CHSQ( 1)= 14.1529 [.000]
F Statistic: F( 1, 43)= 18.5274 [.000]
Appendix 2 Granger causality test

Granger causality
LR Test of Block Granger Non-Causality in the VAR
*******************************************************************************
Based on 46 observations from 1964 to 2009. Order of VAR = 4
List of variables included in the unrestricted VAR:
LCPI    LRW
Maximized value of log-likelihood = -117.7206
*******************************************************************************
List of variable(s) assumed to be "non-causal" under the null hypothesis:
LCPI
Maximized value of log-likelihood = -120.0863
*******************************************************************************
LR test of block non-causality, CHSQ(  4)=   4.7314[.316]
*******************************************************************************
The above statistic is for testing the null hypothesis that the coefficients
of the lagged values of:
LCPI
in the block of equations explaining the variable(s):
LRW
are zero. The maximum order of the lag(s) is 4.
*******************************************************************************

LR Test of Block Granger Non-Causality in the VAR
*******************************************************************************
Based on 46 observations from 1964 to 2009. Order of VAR = 4
List of variables included in the unrestricted VAR:
LCPI    LRW
Maximized value of log-likelihood = -117.7206
*******************************************************************************
List of variable(s) assumed to be "non-causal" under the null hypothesis:
LRW
Maximized value of log-likelihood = -122.4993
*******************************************************************************
LR test of block non-causality, CHSQ(  4)=  9.5574[.049]
*******************************************************************************
The above statistic is for testing the null hypothesis that the coefficients
of the lagged values of:
LRW
in the block of equations explaining the variable(s):
LCPI
are zero. The maximum order of the lag(s) is 4.
*******************************************************************************
LR Test of Block Granger Non-Causality in the VAR
******************************************************
Based on 45 observations from 1965 to 2009. Order of VAR = 4
List of variables included in the unrestricted VAR:
DLCPI  DLRW
Maximized value of log-likelihood = -118.4812
******************************************************
List of variable(s) assumed to be "non-causal" under the null hypothesis:
DLCPI
Maximized value of log-likelihood = -119.3015
******************************************************
LR test of block non-causality, CHSQ(  4)=   1.6406[.801]
*******************************************************************************
The above statistic is for testing the null hypothesis that the coefficients
of the lagged values of:
DLCPI
in the block of equations explaining the variable(s):
DLRW
are zero. The maximum order of the lag(s) is 4.
*******************************************************************************
LR Test of Block Granger Non-Causality in the VAR
******************************************************
Based on 45 observations from 1965 to 2009. Order of VAR = 4
List of variables included in the unrestricted VAR:
DLCPI  DLRW
Maximized value of log-likelihood = -118.4812
******************************************************
List of variable(s) assumed to be "non-causal" under the null hypothesis:
DLRW
Maximized value of log-likelihood = -122.0135
******************************************************
LR test of block non-causality, CHSQ(  4)=   7.0647[.133]
*******************************************************************************
The above statistic is for testing the null hypothesis that the coefficients
of the lagged values of:
DLRW
in the block of equations explaining the variable(s):
DLCPI
are zero. The maximum order of the lag(s) is 4.
*******************************************************************************
LR Test of Block Granger Non-Causality in the VAR
******************************************************
Based on 45 observations from 1965 to 2009. Order of VAR = 4
List of variables included in the unrestricted VAR:
DLRW  DLPROD
Maximized value of log-likelihood = -185.0739
******************************************************************************
List of variable(s) assumed to be "non-causal" under the null hypothesis:
DLPROD
Maximized value of log-likelihood = -187.5924
******************************************************************************
LR test of block non-causality, CHSQ(  4)=   5.0369[.284]
*******************************************************************************
The above statistic is for testing the null hypothesis that the coefficients
of the lagged values of:
DLPROD
in the block of equations explaining the variable(s):
DLRW
are zero. The maximum order of the lag(s) is 4.
LR Test of Block Granger Non-Causality in the VAR
**********************************************************************
Based on 46 observations from 1964 to 2009. Order of VAR = 4
List of variables included in the unrestricted VAR:
LRW LPROD
Maximized value of log-likelihood = -185.4792
**********************************************************************
List of variable(s) assumed to be "non-causal" under the null hypothesis:
LPROD
Maximized value of log-likelihood = -188.4135
**********************************************************************
LR test of block non-causality, CHSQ(  4)=   5.8688 [.209]
**********************************************************************
The above statistic is for testing the null hypothesis that the coefficients
of the lagged values of:
LPROD
in the block of equations explaining the variable(s):
LRW
are zero. The maximum order of the lag(s) is 4.
**********************************************************************

Appendix 3 Unit root tests

Unit root tests

ADF Test for series:      real_wage
sample range:             [1963, 2009], T = 47
lagged differences:       2
intercept, time trend
asymptotic critical values
"Estimation and Inference in Econometrics" p 708, table 20.1,
Oxford University Press, London
1%         5%         10%
-3.96       -3.41       -3.13
value of test statistic: -2.5859
regression results:
---------------------------------------
variable      coefficient   t-statistic
---------------------------------------
x(-1)        -0.2824       -2.5859
dx(-1)        0.2446        1.6202
dx(-2)        0.0087        0.0537
constant      21.0595       2.8098
trend         0.4809        2.5718
RSS            131.2881

OPTIMAL ENDOGENOUS LAGS FROM INFORMATION CRITERIA

sample range:             [1971, 2009], T = 39
optimal number of lags (searched up to 10 lags of 1. differences):
Akaike Info Criterion:  1
Final Prediction Error:  1
Hannan-Quinn Criterion:  0
Schwarz Criterion:       0
ADF Test for series: real_wage_log_d1
sample range: [1964, 2009], T = 46
lagged differences: 2
intercept, time trend
asymptotic critical values
1%  5%  10%
-3.96 -3.41 -3.13
value of test statistic: -3.7255
regression results:

<table>
<thead>
<tr>
<th>variable</th>
<th>coefficient</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>x(-1)</td>
<td>-0.9770</td>
<td>-3.7255</td>
</tr>
<tr>
<td>dx(-1)</td>
<td>0.0500</td>
<td>0.2382</td>
</tr>
<tr>
<td>dx(-2)</td>
<td>-0.0796</td>
<td>-0.5092</td>
</tr>
<tr>
<td>constant</td>
<td>0.0253</td>
<td>3.1793</td>
</tr>
<tr>
<td>trend</td>
<td>-0.0007</td>
<td>-2.1044</td>
</tr>
<tr>
<td>RSS</td>
<td>0.0279</td>
<td></td>
</tr>
</tbody>
</table>

OPTIMAL ENDOGENOUS LAGS FROM INFORMATION CRITERIA

sample range: [1972, 2009], T = 38

optimal number of lags (searched up to 10 lags of 1. differences):
Akaike Info Criterion: 0
Final Prediction Error: 0
Hannan-Quinn Criterion: 0
Schwarz Criterion: 0

ADF Test for series: CPI_log
sample range: [1964, 2009], T = 46
lagged differences: 2
intercept, time trend
asymptotic critical values
1%  5%  10%
-3.96 -3.41 -3.13
value of test statistic: -1.1182
regression results:

<table>
<thead>
<tr>
<th>variable</th>
<th>coefficient</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>x(-1)</td>
<td>-0.0173</td>
<td>-1.1182</td>
</tr>
<tr>
<td>dx(-1)</td>
<td>0.8453</td>
<td>5.6073</td>
</tr>
<tr>
<td>dx(-2)</td>
<td>-0.0500</td>
<td>-0.3167</td>
</tr>
<tr>
<td>constant</td>
<td>0.0759</td>
<td>1.3566</td>
</tr>
<tr>
<td>trend</td>
<td>0.0006</td>
<td>0.5225</td>
</tr>
<tr>
<td>RSS</td>
<td>0.0260</td>
<td></td>
</tr>
</tbody>
</table>

OPTIMAL ENDOGENOUS LAGS FROM INFORMATION CRITERIA

sample range: [1972, 2009], T = 38

optimal number of lags (searched up to 10 lags of 1. differences):
Akaike Info Criterion: 6
Final Prediction Error: 1
Hannan-Quinn Criterion: 1
Schwarz Criterion: 1
DF Test for series: CPI_log_d1
sample range: [1964, 2010], T = 47
lagged differences: 2
intercept, time trend
asymptotic critical values
1% 5% 10%
-3.96 -3.41 -3.13
value of test statistic: -2.4032
regression results:

<table>
<thead>
<tr>
<th>variable</th>
<th>coefficient</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>x(-1)</td>
<td>-0.2326</td>
<td>-2.4032</td>
</tr>
<tr>
<td>dx(-1)</td>
<td>0.1002</td>
<td>0.6746</td>
</tr>
<tr>
<td>dx(-2)</td>
<td>-0.0687</td>
<td>-0.4624</td>
</tr>
<tr>
<td>constant</td>
<td>0.0133</td>
<td>2.0231</td>
</tr>
<tr>
<td>trend</td>
<td>-0.0005</td>
<td>-1.7227</td>
</tr>
<tr>
<td>RSS</td>
<td>0.0269</td>
<td></td>
</tr>
</tbody>
</table>

OPTIMAL ENDOGENOUS LAGS FROM INFORMATION CRITERIA

sample range: [1972, 2010], T = 39

optimal number of lags (searched up to 10 lags of 1. differences):
Akaike Info Criterion: 6
Final Prediction Error: 6
Hannan-Quinn Criterion: 0
Schwarz Criterion: 0

ADF Test for series: CPI_log_d1_d1
sample range: [1966, 2009], T = 44
lagged differences: 2
intercept, time trend
asymptotic critical values
1% 5% 10%
-3.96 -3.41 -3.13
value of test statistic: -7.0234
regression results:

<table>
<thead>
<tr>
<th>variable</th>
<th>coefficient</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>x(-1)</td>
<td>-2.4764</td>
<td>-7.0234</td>
</tr>
<tr>
<td>dx(-1)</td>
<td>0.8551</td>
<td>3.2501</td>
</tr>
<tr>
<td>dx(-2)</td>
<td>0.3935</td>
<td>2.6904</td>
</tr>
<tr>
<td>constant</td>
<td>-0.0005</td>
<td>-0.0947</td>
</tr>
<tr>
<td>trend</td>
<td>0.0000</td>
<td>0.0928</td>
</tr>
<tr>
<td>RSS</td>
<td>0.0408</td>
<td></td>
</tr>
</tbody>
</table>

OPTIMAL ENDOGENOUS LAGS FROM INFORMATION CRITERIA

sample range: [1974, 2009], T = 36

optimal number of lags (searched up to 10 lags of 1. differences):
Akaike Info Criterion: 3
Final Prediction Error: 3
Hannan-Quinn Criterion: 3
Schwarz Criterion: 3
Graphic presentation of the variables
Appendix 4 Test for cointegration

Johansen Trace Test for: CPI_log real_wage_log
sample range: [1961, 2009], T = 49
included lags (levels): 1
dimension of the process: 2
intercept included
response surface computed:

<table>
<thead>
<tr>
<th>r0</th>
<th>LR</th>
<th>pval</th>
<th>90%</th>
<th>95%</th>
<th>99%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>71.27</td>
<td>0.0000</td>
<td>17.98</td>
<td>20.16</td>
<td>24.69</td>
</tr>
<tr>
<td>1</td>
<td>2.65</td>
<td>0.6540</td>
<td>7.60</td>
<td>9.14</td>
<td>12.53</td>
</tr>
</tbody>
</table>

OPTIMAL ENDOGENOUS LAGS FROM INFORMATION CRITERIA

sample range: [1961, 2009], T = 49

optimal number of lags (searched up to 1 lags of levels):
Akaike Info Criterion: 1
Final Prediction Error: 1
Hannan-Quinn Criterion: 1
Schwarz Criterion: 1

*** Tue, 11 Oct 2011 23:20:41 ***

Johansen Trace Test for: CPI_log real_wage_log
sample range: [1961, 2009], T = 49
included lags (levels): 1
dimension of the process: 2
trend and intercept included
response surface computed:

<table>
<thead>
<tr>
<th>r0</th>
<th>LR</th>
<th>pval</th>
<th>90%</th>
<th>95%</th>
<th>99%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>50.61</td>
<td>0.0000</td>
<td>23.32</td>
<td>25.73</td>
<td>30.67</td>
</tr>
<tr>
<td>1</td>
<td>4.97</td>
<td>0.6072</td>
<td>10.68</td>
<td>12.45</td>
<td>16.22</td>
</tr>
</tbody>
</table>

OPTIMAL ENDOGENOUS LAGS FROM INFORMATION CRITERIA

sample range: [1961, 2009], T = 49

optimal number of lags (searched up to 1 lags of levels):
Akaike Info Criterion: 1
Final Prediction Error: 1
Hannan-Quinn Criterion: 1
Schwarz Criterion: 1
VEC REPRESENTATION
endogenous variables:    CPI_log real_wage_log
exogenous variables:     productivity_log
deterministic variables: CONST TREND
endogenous lags (diffs): 0
exogenous lags:           0
sample range:             [1961, 2009], T = 49
estimation procedure:     One stage. Johansen approach

Deterministic term:
----------------------
<table>
<thead>
<tr>
<th>d(CPI_log)  d(real_wage_log)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TREND(t)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

Loading coefficients:
----------------------
<table>
<thead>
<tr>
<th>d(CPI_log)  d(real_wage_log)</th>
</tr>
</thead>
<tbody>
<tr>
<td>ec1(t-1)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

Estimated cointegration relation(s):
-------------------------------------
<table>
<thead>
<tr>
<th>ec1(t-1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CPI_log   (t-1)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>real_wage_log(t-1)</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>CONST</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

VAR REPRESENTATION

modulus of the eigenvalues of the reverse characteristic polynomial:
|z| = ( 1.0000     0.9478     )

Legend:
------
| Equation 1 | Equation 2 | ...
|-------------|------------|---
| Variable 1  | Coefficient | ...
| | (Std. Dev.) | ...
| | {'p - Value'} | ...
| | {'t - Value'} | ...
| Variable 2  | ...

24
Lagged endogenous term:

\[
\begin{array}{c|cc}
\text{CPI\_log} & \text{real\_wage\_log} \\
\hline
\text{CPI\_log}\ (t-1) & 0.895 & -0.031 \\
& (0.008) & (0.008) \\
& \{0.000\} & \{0.000\} \\
& [107.021] & [-3.907] \\
\text{real\_wage\_log}(t-1) & 0.553 & 1.161 \\
& (0.044) & (0.041) \\
& \{0.000\} & \{0.000\} \\
\end{array}
\]

Deterministic term:

\[
\begin{array}{c|cc}
\text{CPI\_log} & \text{real\_wage\_log} \\
\hline
\text{TREND}(t) & -0.010 & -0.003 \\
& (0.000) & (0.000) \\
& \{0.000\} & \{0.000\} \\
& [0.000] & [0.000] \\
\text{CONST} & -1.616 & -0.469 \\
& (0.000) & (0.000) \\
& \{0.000\} & \{0.000\} \\
& [0.000] & [0.000] \\
\end{array}
\]
Residual analysis in VECM
References


3. Heo, S (2003), THE RELATIONSHIP BETWEEN EFFICIENCY WAGES AND PRICE INDEXATION IN A NOMINAL WAGE CONTRACTING MODEL,


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