Unit Labor Costs and Price Level in Slovakia: An Application of Cointegration Analysis

by
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Abstract

The thesis is empirical study of unit labor costs and price level in Slovakia within the cointegration analysis framework. The sample employed in the study covers quarterly data over period 1995-2008. Unit labor costs series for 7 sectors are found to be I(1) process even after allowing for the presence of one structural break. Same result applies also to Consumer price index and Producer price index in Manufacturing and Industry. The results are robust to either using seasonal adjusted data or modeling seasonality using deterministic seasonal dummies. Employing Johansen methodology cointegration relationship between four sectors and CPI are found .Interestingly one of the sectors is Total economy and others are concerned with service provision. Weak exogenity tests suggest that unit labor costs are adjusting to maintain the long run relationship, this results is however sensitive to the exact model specification. Granger causality tests imply causality running from unit labor cost to prices as well as from prices to unit labor costs. However, the information value is contained only in disequilibrium error. These results are sensitive to treatment of seasonality.

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1 Introduction

The search for reliable indicators of inflation has always been of great interest to researchers and wages have been identified as one of possible candidates. Therefore, the effects of change in labor compensation on inflation were researched on theoretical as well as empirical level. The most intuitive logical framework that connects wages and changes in price level is wage price spiral. When excess demand reduces unemployment and the economy is close to it potential output, which is reflected in small output gap, the firms are willing to increase wages in order to attract workers. Moreover, the workers have better negotiation position when asking for higher wages. Higher marginal costs lead to increase in prices of goods and services.

This approach is in line with cost-push model of inflation, which assumes that primary cause of higher prices is higher costs. Labor costs create the major part of the cost of goods and services. In general they contribute to the overall cost by up to 60%; however this figure may vary a lot depending on a particular industry. Therefore it seems tempting to search for causal relationship between wages and prices. However, rise in labor compensation does not have to necessarily lead to higher price level in case it is offset by proportional rise in productivity or squeeze in profits of the companies. Moreover, the price level is usually subject to inflation targeting and therefore active monetary policy may mitigate the inflationary pressure of wages.

The question of interest of this thesis is to determine if unit labor costs, which are measure of productivity adjusted compensation of employees, are related in the long run with the price level measured by consumer price index and how they influence each other in short run. Therefore, the thesis analyzes the empirical relationship between prices and productivity-adjusted wages in Slovakia within cointegration analysis framework. First, time series properties of unit labor costs and different measures of price level are examined, which includes testing the order of integration of each series. Further the joint behavior of the series is analyzed and tests for cointegration are conducted to determine if the series move together in the long run. Finally, causality tests follow and conclude the analysis. These test help better understand nature of joint behavior of the two series in the short run.

Though the empirical analysis of joint behavior of labor costs and price level is not a new topic in the literature the thesis provides an extension of previous studies. Econometric methodology of non stationary time series is advancing and therefore the thesis provides more thorough econometric analysis than previous sectoral studies. Moreover, the thesis analyzes both raw and seasonally adjusted data in order to check the robustness of the result to seasonal adjustment.

The thesis is structured as follows. Chapter 2 provides overview of relevant literature. Chapter 3 summarizes the theoretical framework of the cointegration analysis. Chapter 4 describes the data used in the study. Chapter 5 presents empirical results and their interpretation. The thesis concludes with Chapter 6.

2 Literature review

Prevalent approach in recent literature on empirical analysis of relationship between wage inflation and price inflation[1] is to employ a cointegration analysis, i.e. econometric methodology used to analyze of joint behavior of non-stationary time series.

A first step in the cointegration analysis is to determine the order of the integration of the series, i.e. if they are stationary or if differencing is necessary to achieve stationarity. On this issue conclusion of the literature is quite homogenous and although the studies use different measures of wages and prices they conclude that examined time series are integrated of order one. There are however few exceptions for example Mehra (1991) and Emery and Chang (1996) conclude that price indices are integrated of order two. In the later reexamination of his previous study Mehra (1993) concludes that prices are integrated of order one.

The studies then analyze if the variables move together in the long run and test for existence of cointegration relationship[2]. Existence of such a relationship is confirmed in all studies[3]. Third step is to determine the direction of the Granger causality. Most studies found evidence that prices Granger cause wages. Existence of causal relationship in opposite direction, i.e. wages Granger causing price, is confirmed only by Ghali (1999).

Overall the body of literature published on the topic of empirical relationship between wages and prices can be divided into two main groups: cointegration analysis within the bivariate framework[4] and multivariate framework[5].

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[1] The literature concerned with issue of wage inflation as determinant of price inflation mainly uses productivity-adjusted measure of wages i.e. labor costs. Unit labor costs are then used as the measure of changes in wages in the empirical analysis itself. Therefore the distinction between using term wage price relationship and in fact analyzing unit labor cost-price relationship is not always strictly distinguished.

[2] In multivariate framework not only existence is examined but also the number of cointegration vectors.

[3] Of course except the cases when existence of cointegration relationship is a priori excluded by theory based on the order of integration of the series.

[4] These papers derive the econometric model from microeconomic models, .e.g. modification of dynamic labor demand model (Huh and Trehan, 1995), simple model with firms choosing profit maximizing level of labor (Rissman, 1995) and are not as numerous as their multivariate counterparts.

[5] Multivariate analysis econometric models stem from Expectation Augmented Phillips Curve with different variables proxying for aggregate demand and supply shocks.

Following papers represent the multivariate approach on the issue of empirical relationship between wages and prices. Implication of the augmented Philips-curve model is that prices and productivity-adjusted wages are causally related with bi-directional feedback. This proposition is empirically tested in Mehra (1993) using cointegration and Granger causality tests. His results however indicate causal relationship only from prices to wages. Therefore he concludes that change in unit labor costs is not helpful in predicting future increase in price level.

Ghali (1999) examines the same data as previous studies[6] but comes with different results. Namely, his results support the mark up view of inflation process as implied by expectation augmented Philips curve since according to his study not only prices Granger cause wages but also wages Granger cause prices. So he concludes that unit labor costs are useful in forecasting inflation. Moreover, he finds that wages and prices are cointegrated only when import prices and output gap are included in the long run relationship. The econometric strategy of the paper is to estimate VECM[7] using Johansen approach with four variables: prices[8], labor cost, output gap and import prices.

Interesting results are reported in Breauer (1997). He examines the effect of change in employee compensation on the CPI after 1982 in USA. In his analysis he splits the compensation to various components and disaggregates the CPI index as well. He concludes that if compensation grows in the good producing sectors there is little effect on the overall price level. On the other hand if the compensation increases in service producing segment this increase is then reflected in the prices of certain services and this rise is then passed to prices of goods. Main message of the paper is that following the compensation development in the private services sector is relevant for future path of the inflation.

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[6] Namely US data from 1959Q1:1989Q3, which is a subsample of data 1956Q1: 1992Q4 used previously in Mehra (1993)
[7] Vector Error Correction Model
[8] His study is rather an exception in using GDP deflator as measure of prices; most common is to use CPI.

The studies mentioned above derive the empirical models from the same economic model; however they differ in measures of prices[9], data used as measures of supply shocks and demand pressure. Moreover, Ghali (1999) uses different specification of cointegration relationship with respect to deterministic variables.

Several papers analyze relationship between wage inflation and price inflation within the bivariate framework. This branch is not as extensive as its multivariate framework counterpart. These studies are mainly conducted by different Federal Reserve Banks.

In his first paper on the topic of empirical relationship between wages and prices Mehra (1977) conducted the analysis within the bivariate distributed lag system with the US historical data disaggregated on the level of industries. His results support existence of a bi-directional feedback between average nominal wage and consumer price index. Moreover, he concludes that the causal patterns are not related to the market structure of the industry. However, after Mehra's paper in 1977, whenever the topic of wage inflation as determinant of price inflation is empirically analyzed the researchers use data on unit labor costs, i.e. productivity adjusted employees' compensation and not the nominal wage data.

Rissman (1995) conducts a similar analysis to Mehra (1977) but using the meanwhile developed econometric techniques in analysis of joint behavior of non-stationary time series. She also conducts the analyses on sectoral level but uses unit labor cost instead of nominal wages. Though she uses different price indices her results are robust to the choice of particular price index. Her study found out that in most industries the direction of causality is from prices to wages. However, in case of manufacturing and retail trade unit labor cost Granger cause prices and so have predicting power for future level of inflation.

Much more thorough econometric treatment of the same topic can be found in Emery and Chang (1996). Using aggregated US data from 1957 till 1993 they confirm the results of

[9] Possible options are to use CPI or GDP deflator

previous studies and also conclude that unit labor cost do not exhibit in sample forecasting power for future level of consumer prices. The paper extends the existing literature by examination the stability of relationship between the two time series over time. Moreover, it analyzes the usefulness of unit labor cost as out-of-sample forecaster of inflation. Its results imply that unit labor costs do not substantially decrease the forecast errors of inflation with comparison to univariate model.

Though the bivariate framework does not take into account the effect of other variables, as does the multivariate framework, the results of these studies do not contradict the results of multivariate framework and therefore despite its limitations bivariate analysis may produce useful insight into joint behavior of wages and price. Adopting the bivarate approach the thesis follows the afore mentioned literature to provide the insight into joint behavior of labor costs and pries in Slovakia, which is a representative of small open economy in transition.

3 Theoretical Framework

3.1 Stationary and non-stationary time series

In macroeconomics we mostly encounter non-stationary time series. The differences between stationary and non-stationary time series are quite a few and have important implications for econometric treatment of the data.

Stationary time series exhibits following properties:

- Constant mean
- Finite variance that is time invariant
- Time invariant autocorrelation decreases, i.e. $\rho_k \to 0$ as $k \to \infty$

Properties of the stationary series imply that the time between the series crosses its mean value is finite. Innovation, random shock, to the series has only temporary effect that dies out at certain point. Stationary series is said to be integrated of order zero[10] (hereafter denoted by I(0)).

Non-stationary time series can be characterized as follows:

- Mean is time dependent, the series does not return to any long run mean
- Variance of the series is time dependent and goes to infinity as time approaches infinity, i.e. $\sigma^2_t \to \infty$ as $k \to \infty$
- Theoretical autocorrelation does not decrease[11], i.e. $\rho_k \to 1$ as $k \to \infty$
- Exhibit either deterministic or stochastic trend

Special cases of non-stationary variables are those which can be transformed into stationary by differencing. Integrated and trend stationary variables are such examples. If the series becomes stationary after differencing applied d times we say it is integrated of order d

[10] Terms stationary and integrated of order zero are not equivalent. All stationary process are I (0) but not all I (0) process are stationary.
[11] However, in finite sample correlogram dies out slowly. Therefore slowly decaying correlogram is an indication of unit root process or near unit root process.

(hereafter denoted by I(d)). In more formal way we can say that time series y_t is I(d) if for i= 0, 1,…,d-1 $\Delta^i y_t$ is non-stationary, but $\Delta^d y_t$ is already stationary. . If an integrated series is subject to innovation or random shock its effect is permanent.

If the non-stationarity of the series is not accounted for in the econometric analysis, several problems in econometric modeling may be encountered. Since non-stationary time series exhibit trend, there is a risk of spurious regression[12]. These regressions exhibit extremely high measures of goodness of fit, high t-values and F-value but low Durbin-Watson statistics. In general, conventional statistics are invalid, which makes the interpretation of are not such a regressions very complicated. For example t-ratios do not follow Student-t distribution and therefore the usual tests of significance are not valid. Although it is possible to achieve stationarity by differencing and thereby avoid above mentioned problems, this procedure means loss of long run properties of the time series.

3.2 Unit root tests

In the following section the tests to determine the order of integration of the variables and hence their stationarity will be briefly presented. It is necessary to determine these properties of the time series before further analysis may be performed, since series of different order of integration require different econometric treatment. Prevalent approach to unit root testing is based on Dickey-Fuller types of tests. The thesis also employs this methodology therefore Dickey-Fuller tests are discussed in greater detail in the following subsections.

3.2.1 Dickey-Fuller tests

The Dickey-Fuller testing procedure determines the order of integration of the time series "upwards". So first of all it tests if the series is integrated of order zero. If this does not hold the null hypothesis being tested is whether the series is integrated of order one and so on.

[12] The term of spurious regression refers to regression that does not have meaningful economic interpretation and variables appear to be strongly correlated but only because they follow similar trends.

Assume we have data generating process described by the following equation:

$$y_t = \alpha y_{t-1} + \varepsilon_t, \tag{1}$$

where ε_t is a white noise process. The question of interest is whether coefficient α = 1, and hence the process contains unit root (i.e. the process is non stationary). However, under the null hypothesis of the test y_t is non stationary t statistics of the estimates of the α coefficient do not have an approximate standard normal distribution even in the large samples.

Dickey-Fuller test of unit root slightly modifies (1)[13] and tests the presence of unit root from estimation of one of the following regressions:

$$\Delta y_t = \gamma y_{t-1} + \varepsilon_t \tag{2.1}$$

$$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \varepsilon_t \tag{2.2}$$

$$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \alpha_1 t + \varepsilon_t \tag{2.3}$$

The regressions (2.1)- (2.4) are estimated by OLS and usual t-statistics are computed. The asymptotic distribution of the t-statistics is known as Dickey-Fuller distribution. Using the critical values of this distribution and computed t-statistic on estimate coefficient on y_{t-1}, significance of γ, can be determined. The hypotheses being tested are:

H0: $\gamma = 0$, i.e. y_t contains unit root and hence it is not stationary

H1: $\gamma < 0$, i.e. y_t is stationary

Critical values for each of the equations (2.1) - (2.3) were simulated separately. The more deterministic components are included into the model the greater are the critical values in absolute value. Estimating model (2.1) implies assumption that the starting value of the series is equal to zero. To allow for non zero initial observation constant is included into the model (2.1) and model (2.2) is estimated.

[13] We subtract y_{t-1} from both sides of (1). So $\gamma = \alpha - 1$.

3.2.1.1 Augmented Dickey Fuller test

If the data generating process does not take the form as in (1), but instead could be better modeled as an autoregressive process of order p, error terms in (1) would suffer from serial autocorrelation. Therefore in case y_t follows AR(p) process Augmented Dickey Fuller test is preferred. Lagged first differences are added to the regressions (2.1) - (2.3). Since distribution of the t-statistics does not depend on the number of lagged values critical values for simple Dickey-Fuller test are applicable.

$$\Delta y_t = \gamma y_{t-1} + \sum_{i=1}^{p-1} \beta_i \Delta y_{t-i1} + \varepsilon_t \quad (3.1)$$

$$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \sum_{i=1}^{p-1} \beta_i \Delta y_{t-i} + \varepsilon_t \quad (3.2)$$

$$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \alpha_1 t + \sum_{i=1}^{p-1} \beta_i \Delta y_{t-i} + \varepsilon_t \quad (3.3)$$

In case when true data generating process is unknown, according to Harris (1995), the most general model, i.e. (3.3) should be estimated. Choosing the model including constant and deterministic trend means t_τ [14] critical value of DF distribution has to be used, which is the one furthest away from zero. Therefore, t-statistics from the model, which included both deterministic components, are less likely to indicate rejection of the null hypothesis. So, we are more likely to conclude that the data generating process is non-stationary when we include more deterministic components into the model. On the other hand, the estimated model, used for testing has to nest the null as well as the alternative hypothesis. This requirement implies

[14] The standard notation uses the τ for critical values for models (2.1),(3.1); τ_μ for models (2.2),(3.2); τ_τ for models (2.3),(3.3)

that the model should include more deterministic components that unknown data generating process[15].

Another issue in practical application of ADF test is the choice of the number of lagged first differences included in the model. The test requires fully specifying the dynamics of the model (i.e. include more lags). However, increasing number of lags decreases the power of the test. One option is to include the minimal number of lags to ensure that error terms in the model are not serially correlated. It is also possible to determine the length of the lags included in the model on the basis of the frequency of the data[16]. Popular approach is also to use some of the model selection criteria[17] for the choice of the lag length and then test the errors for presence of serial autocorrelation in the residuals.

One of the most serious limitations of the unit root tests is their low power[18]. These tests have problems to distinguish unit root process from near unit root process and too often they imply that time series is a unit root process. Power of these tests to correctly determine whether true data generating process is trend stationary[19] or drifting is also low.

Further more, unit root tests are sensitive to the choice of deterministic components (i.e. intercept, deterministic trend). It may be tempting to estimate the most general model, i.e. one including intercept and time trend. However, this approach is very costly in terms of degrees of freedom and power of the test. The presence of unnecessary deterministic trend and drift term reduce the power of the test. The problem is that tests of unit roots are conditional on the presence of deterministic components and testing the presence of

[15] It is not necessary to include more deterministic components than constant and trend, e.g. t^2. Significant trend in e.g. (2.3), (3.3) implies (in case y_t is in logarithmic form) ever increasing rate of change which is not really plausible assumption about data generating process. Therefore presence of deterministic trend in case of unit root process is a priory precluded.

[16] For annual data usually one or two lags are included. For quarterly data usually four lags are included.

[17] For example Final Error Prediction Criterion or Schwarz Information Criterion

[18] Power of the test refers to the probability that false null hypothesis will be rejected. This probability can be expressed as (1-probability of a Type II. Error)

[19] In finite sample any trend stationary process may be approximated by unit root process as well as other way around.

deterministic repressors depends whether the series has a unit root or not. Enders (1993) discusses the guidelines that may help the correct identification which deterministic components are part of true data generating process, in case this process is completely unknown[20]. Moreover he implies that there is no certain procedure how to reliably determine the correct deterministic repressors and look at the plotted data as well as theoretical consideration should suggest appropriate repressors.

3.2.2 Unit roots in presence of seasonality

As discussed in Harris (1995) seasonal adjustment filters impose distortion on the data generating process. From the point of view of unit root testing the most important consequence of this distortion is that estimate of coefficient on lagged value of time series[21] in ADF test is biased towards one. Therefore, the series tested is more likely to be considered non-stationary than it should according to the critical values of Dickey-Fuller distribution.

To test seasonally unadjusted data for presence of standard unit root, i.e. unit root at zero frequency, model (4) is estimated.

$$\Delta y_t = \alpha_1 D_1 + \alpha_2 D_2 + \alpha_3 D_3 + \alpha_4 D_4 + \alpha_5 t + \gamma^* y_{t-1} + \sum_{i=1}^{p-1} \beta_i^* \Delta y_{t-i} + \varepsilon_t , \quad (4)$$
$$\varepsilon_t \sim N(0,\sigma^2)$$

where D_i are seasonal dummies equal to one in *i*-th quarter. As mentioned previously in case of standard ADF test both hypotheses have to be nested in the estimated model, therefore we included all 4 seasonal dummies and trend. Including the afore mentioned deterministic components makes the test invariant to the drift parameter and starting value of the examined time series, y_0.

[20] The procedure is based on sequential testing of significance of the deterministic variables using corresponding critical values.

[21] In the notation of the previous section the coefficient on $y_{t'-1}$ was denoted by γ.

In case when data have a strong seasonal pattern that is not constant over time, literature suggests amending the ADF test to allow for additional unit roots at seasonal frequency. In order to impose the less restrictive assumption on seasonal pattern of true data generating process and assume non-stationary (time varying) seasonal pattern the equation (5) can be estimated using raw data.

$$(1-L)(1-L^4)y_t = \Delta\Delta_4 y_t = \alpha_1 D_1 + \alpha_2 D_2 + \alpha_3 D_3 + \alpha_4 D_4 + \beta_1 \Delta_4 y_{t-1} + \beta_2 \Delta_4 y_{t-2} + \sum_{i=1}^{p-1} \psi_i^* \Delta\Delta_4 y_{t-i} + u_t \qquad (5)$$

However, as stated in Harris (1995) if stationarity can be achieved by first differencing imposing deterministic seasonal pattern is acceptable. Therefore, we omit seasonal unit root testing from further discussion.

To summarize, when testing the time series for presence of unit root we may encounter three scenarios. Either working with seasonally adjusted data and use standard unit root tests mentioned in section 3.2.1 or if there are raw data available either assumption that seasonal pattern is stationary can be imposed and follow test described by model (4) or allow for the least restrictive assumption and test the series for presence of unit root at other than only zero frequency as mentioned suggested by model (5).

3.2.3 Unit root test in the presence of structural break

If the series has undergone an isolated change in its data generating process we speak about structural break. The literature recognizes that presence of structural break in the deterministic components can affect the ADF unit root test results. The standard ADF test is likely to identify stationary or trend-stationary series as non-stationary when in fact it has undergone permanent break in some of its deterministic components. Finding that presence of structural break significantly decreases power of unit root test is supported by several studies summarized in Rao (2007).

When dealing with structural breaks there is always an option to treat the break as exogenous, i.e. determined ex ante by researcher based on economic information, or as endogenous, i.e. unknown[22]. Since determination of break point exogenously may lead to the power distortion in a way that the test over rejects the null hypothesis the endogenous determination of the break point is preferred (Rao, 2007).

The modeling strategy of endogenous treatment of the structural break point is to test each of the possible break points. Then chose as a break point the one, where the evidence against the null hypothesis is the strongest. So, break point is determined by t-statistics on the coefficient on lagged value of the examined series in unit root test. However, these t-values do have neither standard-distribution nor Dickey-Fuller distribution.

Literature following approach introduced in Perron (1989) suggests three models allowing for one structural change in mean or slope or both deterministic components of the time series. Equations (6.1)-(6.3) represent these models.

$$\Delta y_t = \alpha_0 + \alpha_1 D_t(TB) + \gamma y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta y_{t-i} + \varepsilon_t \tag{6.1}$$

$$\Delta y_t = \alpha_0 + \alpha_2 t + \alpha_3 (t - TB) D_t(TB) + \gamma y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta y_{t-i} + \varepsilon_t \tag{6.2}$$

$$\Delta y_t = \alpha_0 + \alpha_1 D_t(TB) + \alpha_2 t + \alpha_3 (t - TB) D_t(TB) + \gamma y_{t-1} + \sum_{i=1}^{k} \beta_i \Delta y_{t-i} + \varepsilon_t \tag{6.3}$$

,where $D_t(TB)$ is dummy variable defined as follows: $D_t(TB) = \begin{cases} 0 & t < TB \\ 1 & t \geq TB \end{cases}$.

Although the model (6.3) can capture the changes in data generating process more flexibly, as mentioned earlier, increasing number of deterministic components decreases the critical values and so makes rejection of the null hypothesis of non-stationarity less likely.

[22] There is a body of literature on models allowing for multiple structural break, however due to the very small sample size possibility for multiple structural breaks is omitted from further analysis.

3.3 Cointegration

Econometric analysis without accounting for non-stationarity of the series, if present, gives a rise to major problems like invalid t-statistics and danger of spurious regressions. In case of I(d) variables these complications can be avoided by differencing the series d times and thereby achieving stationarity. However, this procedure leads to loss of the information on long-term dynamics[23] of the series. Cointegration is concept that allows estimating models that maintain the short run as well as long run properties of the series while dealing only with stationary variables.

If there are series that are non-stationary but their linear combination is stationary we say that these series are cointegrated. The existence of cointegration relationship is interpreted as existence of long run equilibrium among the cointegrated variables.

The term equilibrium has a slightly different meaning for econometricians and for economics theorists. The first group understands under term equilibrium long run relationship among non-stationary variables. However, for the economic theorists equilibrium is equality between desired and actual transactions. Moreover, they assume that the equilibrium relationship is result of market forces or behavioral patterns of agents. On the other hand in the econometrician’s understanding of the term, represented by Engle and Granger’s view, the long term relationship among variables may be casual, behavioral or reduced form relationship among variables with similar trend (Enders 1993).

3.3.1 Engle – Granger approach

The formal definition of cointegration was introduced by Engle and Granger (1987). Assume $n \times 1$ dimensional vector z_t consisting of n time series $y_{1t},...,y_{nt}$ such that:

-each series y_{it} is I(d)

[23] Some models expressed in first differences of non-stationary variables might not even have a long run solution

-there exists an $n \times 1$ vector β such that $z_t'\beta \sim I(d-b)$, where $b > 0$

then series $y_{1t},...,y_{nt}$ are said to be cointegrated denoted by $z_t'\beta \sim CI(d,b)$. Vector β is called cointegration vector. Linear relationship $z_t'\beta = u_t$ is referred to as long run equilibrium. Series u_t is called disequilibrium error and by definition of cointegration is u_t stationary.

To estimate the cointegration vector in two variable case Engle and Granger methodology may be used. The procedure is simple and requires only regressing one series on the other and testing the stationarity of the residuals of the regression using for example ADF test. Though this methodology enables estimating the cointegration vector is does not allow testing if the estimates of cointegration coefficients are significantly different from zero. Moreover, is only applicable in bivariate case.

3.3.2 Johansen approach

The most commonly used procedure for testing for cointegration is the Johansen approach. This methodology not only allows for testing the existence of cointegration relationships in multivariate case but is also asymptotically efficient in contrast to Engle-Granger methodology.

Denote z_t a vector of n endogenous variables and assume that z_t can be modeled[24] by unrestricted vector autoregression (VAR)

$$z_t = A_1 z_{t-1} + ... + A_k z_{t-k} + u_t \qquad u_t \sim IN(0,\Sigma), \tag{7}$$

where z_t is vector of dimension $n \times 1$ and A_i is an matrix of parameters with dimension $n \times n$. For the purpose of cointegration analysis the equation (7) is rearranged into model (8)

$$\Delta z_t = \Gamma_1 \Delta z_{t-1} + ... + \Gamma_{k-1} \Delta z_{t-k+1} + \Pi_k z_{t-k} + u_t \tag{8}$$

[24] The advantage of VAR modeling is that is does not require imposing a priori assumption on structural relationships as well as endgenity or exogenity of series comprising vector z_t. Moreover, VAR can be efficiently estimated by OLS procedure.

where $\Gamma_i = -(I - \sum_{j=1}^{i} A_i)$ for $i = 1,...,k-1$, and $\Pi = -(I - \sum_{j=1}^{k} A_i)$.

Granger Representation Theorem states that in case the coefficient matrix Π has rank $r < n$, then Π can be expressed as product of matrices α and β, each of dimension $n \times r$, with rank r and $\beta' z_t \sim I(0)$. The number of cointegration relationships r is called cointegration rank. Interpretation of the decomposition of the matrix Π as product of matrices α and β, i.e. $\Pi = \alpha' \beta$, is as follows. Vector α can be interpreted as speed of adjustment to disequilibrium error and β is matrix of long-run coefficients ensuring stationary linear combination among series. Columns of matrix β represent the cointegration vectors. Equation (8) is referred to as a Vector Error Correction Model (VECM). The important property of this model is that the lagged differences terms enable to capture short run effects and Π contains information on long run dynamics of the variables.

In multivariate case of *n* series there can exist as many as *n*-1 cointegration vectors and testing for the number of existing cointegration vectors among series in vector z is done by determining the rank of matrix Π[25], estimated from model (8). Three cases are possible:

i. $r = 0$ implies there does not exist any linear combination of series in z that is stationary, i.e. variables in z are not cointegrated.

ii. $r \leq n-1$ suggests that there exist r cointegrating vectors between the variables in z.

iii. $r = n$ represents the case when matrix Π has a full rank, what implies that variables are stationary. However, since pretesting for unit root is necessary and all series in z are I(1)[26]. Therefore result that matrix has full rank Π may indicate either incorrect estimation of order of integration of some of the series in z or commitment of Type I error by cointegration rank test. Furthermore, these results may also indicate the

[25] The rank of Π is always reduced except the cases when all the variables are stationary (then Π has full rank) or there is no cointegration among series in vector z (Π is in this case zero matrix)
[26] We don not discuss the treatment of series of higher order of integration here.

structural break in the data, local outliers or other problem in the data that has not been accounted for appropriately.

The Johansen test for the cointegration rank of the matrix Π uses fact that rank of the matrix is equal to the number of non-zero eigen values λ_i. Therefore the following two test statistics are constructed to determine the *r*.

$$\lambda_{trace}(r,n) = -T\sum_{i=r+1}^{n}\log(1-\lambda_i) \tag{9}$$

$$\lambda_{\max}(r,r+1) = -T\log(1-\lambda_{r+1}), \tag{10}$$

where *T* denotes the sample size and λ_i eigen values of the matrix Π in descending order, i.e. $\lambda_1 > \lambda_2 > ... > \lambda_n$.

Statistics λ_{trace} test the null hypothesis that there are at most *r* cointegration vectors, which implies existence of *(n-r)* unit roots. The test sequentially tests different values of *r* starting with $r \le 0$ up to $r \le n-1$.

$$H_0 : \lambda_i = 0 \quad i = r+1,...n$$

Statistics $\lambda_{\max}$ test the null of existence of r cointegration vectors against alternative that *r+1* cointegration vectors exist. The λ_{trace} and $\lambda_{\max}$ statistics follow special distribution and critical values can be found for example in Osterwald-Lenum (1992). Critical values are robust to inclusion of seasonal dummies that sum up to zero over time (Harris 1995). However, other types of dummy variables affect the underlying distribution of the test statistics. Therefore if policy dummies are added to the estimated model critical values are only indicative.

Once the number of cointegration vectors is determined the dimensions of the matrix β and α are know. By testing if there is a zero row in matrix α it can be specified which variable is the source of the force that drives the long run relationship. Variable which correspond to the zero row in α is said to be weakly exogenous for long run parameters constituting columns in β. If variable is weakly exogenous for cointegration relationship parameters it means that the variable influences the path of the other variables included in the long rum equilibrium but it is not influenced by them. The weakly exogenous variable is taken as given and other variables need to adjust so that the cointegration relationship holds.

3.4 Causality

On its most intuitive level the concept of causality between wages and prices refers to the question whether increase in prices results in increase in wages when otherwise they would have remained the same. However, in empirical econometrics one needs to transform this intuitive understanding of causality into more operational definition.

The most used definition of causality is the Granger definition of the concept as introduced in Granger (1969). Lets assume two variables x and y. We say that x Granger causes y (hereafter denoted as $x \rightarrow y$) if current value of y can be predicted more accurately using past values of x rather than leaving them out, other information being equal. Besides Granger causality mentioned above one may distinguish also the concept of instantaneous causation (hereafter denoted as x => y). We say that x is instantaneous cause of y if present and past values of x help better predict y other information being identical[27].

Before stating the formal and also testable definition of the causality concepts we following notation is introduced: let U_t be the information set of all present and past information existing at time t[28]. Let X_t denote information set consisting of past and preset values of variable x[29]. Further we denote y_t current value of y and $\tilde{y}_t$ an unbiased prediction

[27] To define concept of instantaneous causation is only possible because in practice we always have a set of discrete observations of x and y.instead of continuous. If we had continuous observations of variables we could not speak of instantaneous causation because there is always time difference between independent actions.
[28] The concept of “all information” is not well defined and in practice is translated as “all relevant information” which is however still upon arbitrary decision of the researcher.
[29] Clearly X_t is subset of U_t

of y_t. MSE stands for mean square error of prediction of y_t. Using above introduced notation formal definition of causality concepts maybe stated as follows.

Granger causality:

We say x Granger causes y, **x→y**, if $MSE(\tilde{y}_t | U_{t-1}) < MSE(\tilde{y}_t | U_{t-1} \setminus X_{t-1})$

Granger instantaneous causality:

We say x Granger instantaneously causes y, **x=>y**, if $MSE(\tilde{y}_t | U_t \setminus y_t) < MSE(\tilde{y}_t | U_{t-1} \setminus X_t, y_t)$

Two most commonly used tests for causality are operational formulations of the concept of causality as described before They are later modification of the early work of Granger (1969) further elaborated by Sargent (1976), known as Granger test, and Sims (1972), known as Sims-GMD test.

3.4.1 Granger test

The test of causality between two variables x and y is based on estimating unrestricted bivariate VAR model as given by equation (11)[30] and testing the joint significance of coefficients on past values of variable x.

$$y_t = A_0 D_t + \sum_{i=1}^{k} \alpha_i y_{t-i} + \sum_{i=1}^{k} \beta_i x_{t-i} + \varepsilon_t \qquad (11)$$

D_t stands for deterministic variables like intercept, deterministic trend and seasonal dummies, A_0 is vector of coefficients of deterministic variables.

After estimating the model (11) F-test or Lagrange Multiplier LM test can be used to test the null hypothesis of no causality in Granger sense.

[30] Model is underlay by assumption that all variables that are included are stationary, or more precisely integrated of order zero. We present the modification of basic model in case of non-stationary variables in the section with empirical results.

H₀: x does not Granger cause y , $\beta_1 = \beta_2 = ... = \beta_k = 0$

H₁: x does Granger cause y , $\exists\, i\ \beta_i \neq 0$.

3.4.2 Sims-GMD test

The test was introduced in the paper by Sims (1972) and was later further developed by Geweke, Meese and Dent (1983). Intuitively present values can not be caused by future values. This general implication of causality was developed into formal test. In fact the test tests if the necessary condition for x not causing y holds.

In order to determine whether x Granger causes y . following model is estimated:

$$x_t = A_0 D_t + \sum_{i=1}^{k} \gamma_i x_{t-i} + \sum_{\substack{i=-m \\ i \neq 0}}^{k} \delta_i y_{t-i} + \upsilon_t \qquad (12)$$

The model (12) resembles to VAR for variable x_t but it includes also leading values of y_t . Note that current value of y , i.e. y_t is excluded. In order to test the null hypothesis of no causality joint significance of coefficients on leading values of variable y_t i.e. δ_s is tested.

H₀: x does not Granger cause y , $\delta_{-1} = \delta_{-2} = ... = \delta_{-m} = 0$

H₁: x does Granger cause y , $\exists\, i$, *-m<i<-1*, $\delta_i \neq 0$

Originally the above-mentioned tests were developed for stationary variables. As stated in Harris (1995) it is not recommended to use LM-type tests in models where variables integrated of order one are included. Therefore in case of non-stationary series the models are estimated using differences of the series, so that they became stationary and adding cointegration relationships into the model if they are present between the variables.

To compare the two above-mentioned tests is not straight forward since they are based on slightly different philosophical notion of causality. One obvious disadvantage of the Sims-

GMD test is that since it uses also the leads of variable y it consumes more observations; therefore in small samples it may be too costly in terms of the loss of degrees of freedom.

When results of the causality are being interpreted one has to be aware of their drawbacks as well as general limitations of Granger causality analysis to avoid misleading interpretation. First of all, the Granger causality may not imply true causality. Since the notion of causality as perceived by statisticians is not connected with any theoretical causality one may encounter the rooster and sunrise problem. One can hear roosters crow before sunrise and so the crow contains information about the time when sun comes up. However, we cannot argue that rooster's crow causes the sunrise.

Another case when detected Granger causality may be misleading is for example if both variables, x and y, are driven by values of third variable z. The tests of Granger causality will detect the causality between x and y even though altering one series would not have an impact on the other series. In fact x may only be proxing effect of z on y.

4 Data description

4.1 Unit labor costs indices time series

In this thesis quarterly data on Unit labor costs provided by OECD[31] are used. For Slovakia the published time series start from 1995Q1. The most recent observation available is 2008Q3. So, the sample used for the thesis includes 55 observations. Since seasonally adjusted as well as raw data are available in the index form both of them are used.

Unit labor costs measure the average cost of labor per unit of output. In index form they can be calculated using following formula:

$$ULC_t = \left[\left(\frac{\dfrac{Employee\ compensation\ total_t}{Hours\ worked\ \ per\ employee_t}}{\dfrac{GDP\ in\ real\ \ prices_t}{Hours\ worked\ \ total_t}} \right) : \left(\frac{\dfrac{Employee\ compensation\ total_{2005}}{Hours\ worked\ \ per\ employee_{2005}}}{\dfrac{GDP\ in\ real\ \ prices_{2005}}{Hours\ worked\ \ total_{2005}}} \right) \right] * 100$$

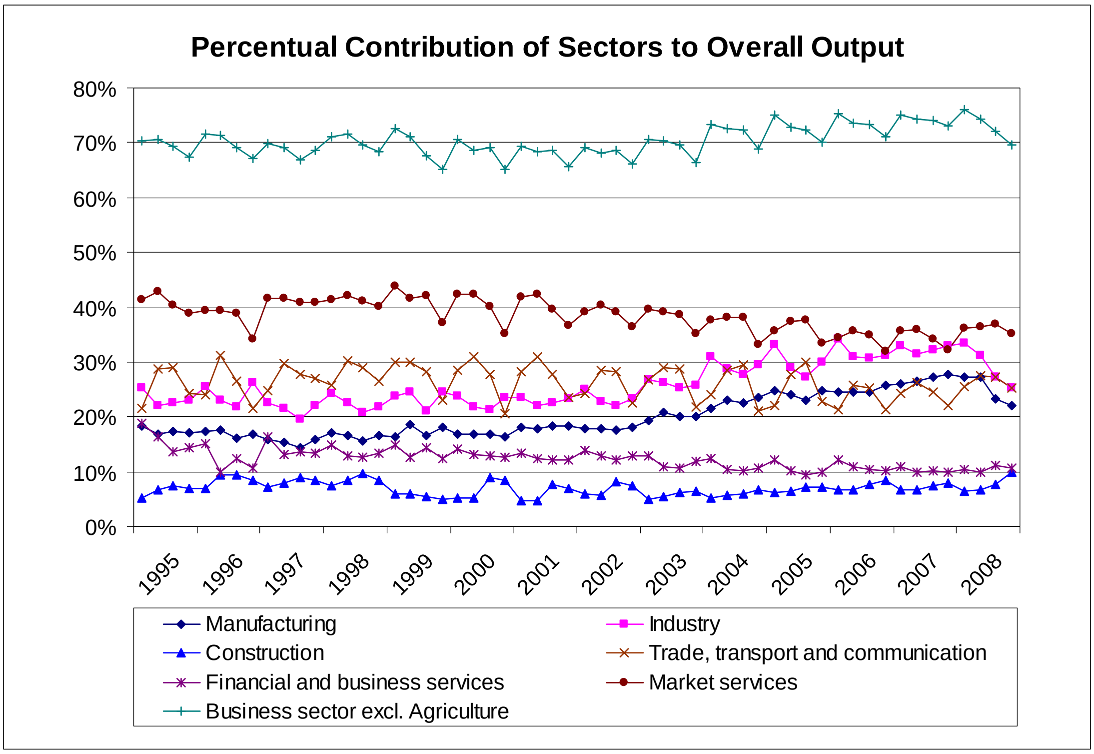
Employee compensation is more extensive concept than wage, since compensation includes full cost of employee for the employer. Therefore it comprises not only the wage but also the contributions to social security systems. For illustration, since 2005 the tax wedge between labor costs and net wage is around 38% in Slovakia. So, the net income of the employee amount to slightly more than 60% of labor costs. Therefore, increase in labor compensation might not be reflected in increase in the nominal wage, but only in change in income taxes or social security contribution.

Unit labor costs are in fact measuring the difference between compensation growth and productivity growth. Increase in unit labor costs indicates that the employee compensation is growing faster then their productivity. Whereas decrease in unit labor cost appears when wage increase lags the productivity increase.

The thesis follows the behavior of the unit labor costs index in 7 sectors, namely Manufacturing (hereafter Man), Industry (In), Construction (Conn), Trade, transport and communication (TTC), Financial and business services (Fin), Market services (Mar) and Business sector excluding agriculture (Bus). The economic activities are assigned to particular sector according to the methodology of International organization of labor[32]. The sectoral division is not mutually exclusive.

Figure 1 plots the percentual contribution of sectors to overall output of the economy. As can be seen in the graph the contribution of particular sectors to the overall output of the whole economy is quite stable over the sample period. Although slight increase can be observed in sectors like Manufacturing and Industry. On the other hand, slightly decreasing contribution of the Trade, transport and communication can be spotted from the Figure 1. Business sector excluding agriculture is fairly aggregated measure as it includes more than 70% of all economic activities.

Figure 1 Percentual contribution of sectors to overall output



Data source:Eurostat

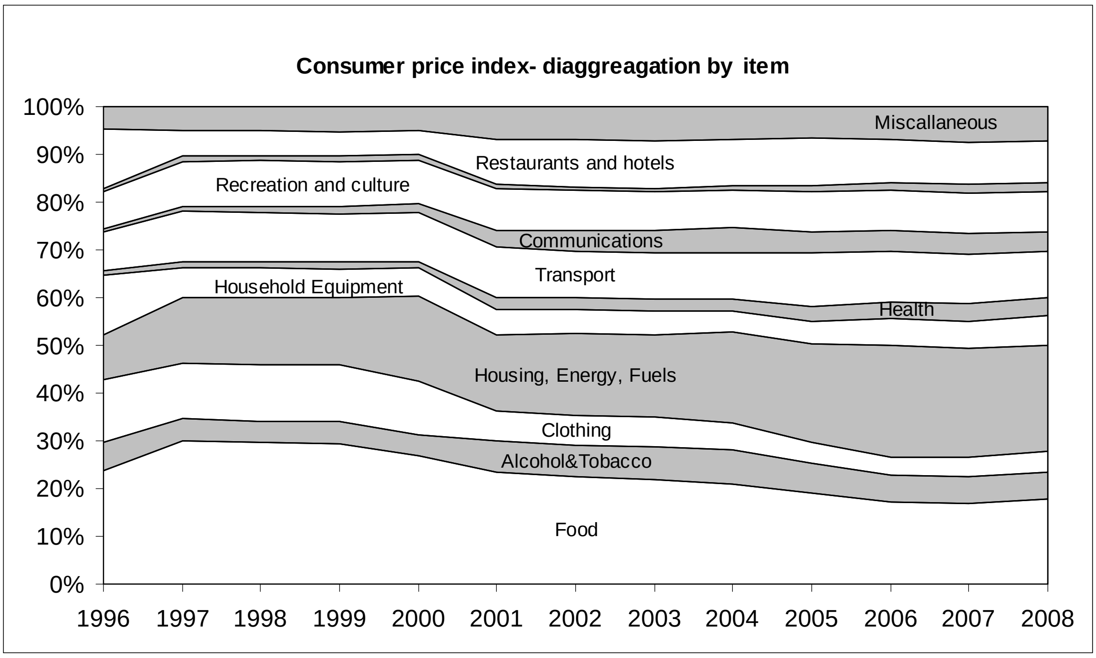
[32] http://www.ilo.org/public/english/bureau/stat/class/isic.htm

4.2 Price indices time series

The data on prices also come from the OECD database. The thesis employs three price indices: Consumer price index, Producer price index for Industry and Producer price index for Manufacturing. Time series used start in 1995Q1 and are available till 2008Q3. OECD database provides price indices only as seasonally unadjusted series. For seasonal adjustment X-11 procedure was used.

The Consumer price index is used as a measure of the overall price level[33]. It also subject to inflation targeting and therefore the reference price level for inflation reported by Statistical office in Slovakia. The Figure 2 plots the dynamics of the components of the consumer basket in Slovakia from 1996 to 2008. The graph shows in case of items like communication and recreation and restaurants the share of the components has significantly increase in 2001. The share of food in the price index is decreasing steadily.

Figure 2 Consumer basket components by item



Data source:Eurostat

[33] In general CPI might be strongly influenced by changes in prices of food and fuel and therefore it may be seen as noisy when we look on the impact of unit labour costs on price level. On the other hand the wages and inflationary expectations are based on the actual CPI index and not the core CPI index therefore when examining the effect of changes in price level on wages and hence unit labor costs CPI is more appropriate measure.

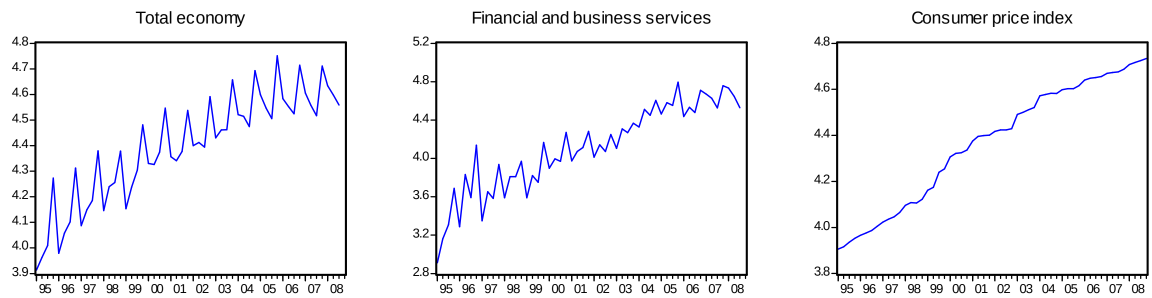
Produce price index for particular sector is measuring prices of goods and services either as they leave the place of production or as they enter as inputs into the production process. Therefore the index is indication of changes in prices received by domestic producers for their outputs or cost of intermediate goods entering production. In case of Slovakia the producer price index is based on prices of industrial goods, manufactured in Slovak republic. The prices exclude Value added tax, but include the consumption tax. For the purpose of the further analyses these price indices may better reflect the true cost of goods produced in particular sector and therefore capture the inflationary pressure of change in unit labor cost on price of output more precisely than overall price index. Unfortunately these indices are available only for two sectors. For other industries no more specific price measures were available.

5 Empirical results

5.1 Preliminary look at the data

The plot of the unit labor cost series can be found in Figure 6 and Figure 8[34] in Appendix1. Price indices are plotted in Figure 7. It can be seen that unit labor costs series exhibit a strong seasonal pattern. For some series like Total economy, or Trade, transport and communication the seasonality appears to be unchanged over the sample period. On the other hand seasonality in Financial service sector and construction is very irregular and changing during the sample period. Looking separately at series of output and compensation one may conclude that the seasonality of unit labor cost data is mainly due to seasonal variation of output. Seasonal pattern in case of price indices does not appear to be strong. Seasonal patter of selected series is illustrated by Figure 3.

Figure 3 Seasonality – selected series – raw data



One interesting property of unit labor costs series is that level of the series seems to be converging to the Total economy unit labor costs and from 2004 on unit labor costs across all sectors oscillate around their level. This can be well seen in Figure 4 where the thick solid line represents the Total economy unit labor costs. The only two sectors where unit labor costs were initially above the level of unit labor costs in total economy are Industry and Manufacturing.

34 All series were logaritmized. For the sake of simplifying the notation we only use the name of the series without indicating that it is actually log of the series.

Figure 4 **Unit labor costs 1995-2008 – seasonally adjusted data**

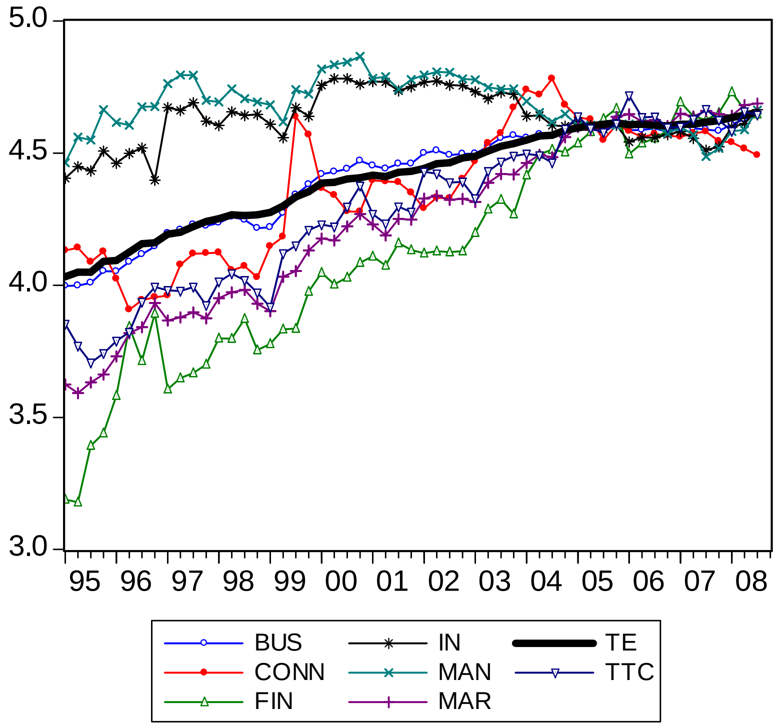
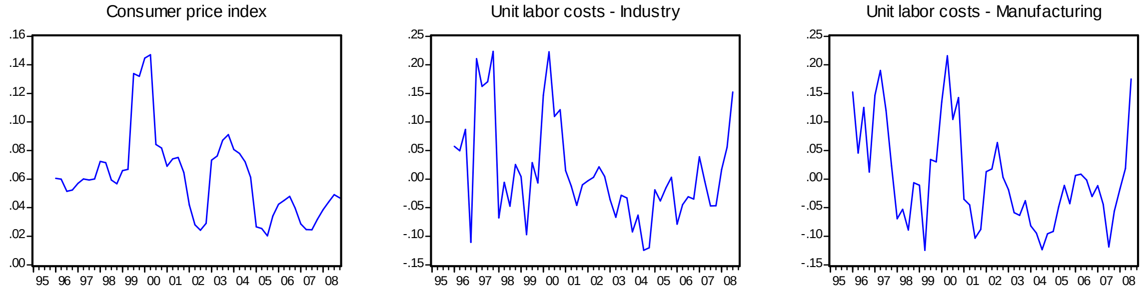


Figure 10 in Apendix1 plots the year-over-year differences of unit labor costs series and price indices series. Based on the graphs it is hard to tell if changes in unit labor costs series are moving together with the changes in price level. However, we may note that variability of the labor cost series is much larger when compared to changes in CPI series.

Figure 5 **Year-over-year differences –selected series**



The changes on year-over-year basis in CPI are always positive and no larger than 10%. The only exceptions are four quarters of inflation around 14% around break of the years 1999/2000. This peak in the year to year change in the CPI series may be attributed to change in the Value added tax rate and change in Import surcharges (Hajnovič 2001). On the other hand after entering the ERM II mechanism in 2005 the inflation level was stabilized and remained bellow 4% level. It is also interesting to note than unit labor costs in manufacturing and industry sectors exhibit negative year-to-year change from 2001 on. The change in the dynamics came only in 2008 when first time after 7 years the productivity adjusted wage growth was positive.

5.2 Unit root testing

The first step in the analysis of the data is to determine the order of integration of the series. Since ADF test is the prevalent testing procedure in the literature we use this test and its modifications to test for the presence of the unit root. Following recommendations of Mehra (1993) we can conclude that the data generating process of the time series is I(0) only if the hypothesis that the series is I(1) is rejected and also the hypothesis that the series is trend stationary is also rejected. Further on both seasonally adjusted data and seasonally unadjusted data. are analyzed in order to see the robustness of the results to seasonal adjustment.

5.2.1 Standard ADF with raw and seasonally adjusted data

For further analysis it is necessary to determine if the levels or differences of the examined series are stationary. Table 1 presents the result of the standard ADF test build in E-Views 5.1. The number of lags is by default chosen by Schwartz information criterion. Similar to Emery and Chang (1998) we check for the serial autocorrelation of the errors in the chosen model using Ljung-Box Q-statistics. If the hypothesis of no serial autocorrelation cannot be rejected the model with next lowest Schwartz information criterion is picked and results for that model are reported. Tests were performed with seasonally adjusted data in levels and 1st differences. Panel A in Table 1 presents t-statistics of estimates of coefficient γ in equation (2.3) and (3.3), respectively.

As argued in Lopes (2006), inter alia, applying ADF test to seasonally adjusted data lowers the power of the unit root tests. Furthermore, he reports the conclusion of recent literature on the properties of ADF test when non-stationary seasonality is neglected and states that even though data generating process may contain seasonal unit roots ADF can still be used validly if sufficient number of lagged differences is included to account for these non stationary components. In order to conduct the unit root test with seasonally not adjusted data seasonal dummies are included into the estimated models. Table 1 summarizes also the results of unit root tests of seasonally not adjusted unit labor cost and price series. The equation (13) and (14) were estimated to obtain t-statistics on estimates of γ reported in Panel B.

$$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \alpha_2 D_2 + \alpha_3 D_3 + \alpha_4 D_4 + \sum_{i=2}^{k} \beta_i \Delta y_{t-i+1} + \varepsilon_t \tag{13}$$

$$\Delta y_t = \alpha_0 + \gamma y_{t-1} + \alpha_1 t + \alpha_2 D_2 + \alpha_3 D_3 + \alpha_4 D_4 + \sum_{i=2}^{k} \beta_i \Delta y_{t-i+1} + \varepsilon_t \tag{14}$$

The results of the unit root tests are reported in Table 1. They indicate that for the levels of the series the null hypothesis of presence of unit root can not be rejected. The opposite is true for the first difference of the series and therefore the unit root tests suggest that the series are I(1). The implications of the unit roots test are robust to use of seasonally adjusted or raw data with deterministic seasonal dummies.

The only exception is series Fin. In case of this series drawing conclusion from the results reported in Table 1 is not so straightforward. On one hand, standard ADF test rejects the hypothesis of a unit root. On the other hand using raw data with seasonal dummies does not reject the null hypothesis. By using seasonal dummies to account for the seasonal pattern in the series we implicitly impose assumption that seasonality remains constant over sample period. However, graph of the series Fin plotted in Figure 3 suggests that this is not really a plausible assumption, what would favor implication of standard ADF test. Moreover, the tests give also different results for first difference of the series Fin. Standard ADF

Table 1 **Unit root tests with raw and seasonally adjusted data**

	Panel A						Panel B					
	Augmented Dickey-Fuller test						Augmented Dickey-Fuller test with deterministic seasonal dummies					
		t-statistics						t-statistics				
Series	**lags**	**trend, constant**		**lags**	**constant**		**lags**	**trend, constant**		**lags**	**constant**	
Bus	0	-1.390		0	-2.346		4	-2.329		4	-2.596	
Conn	0	-2.255		0	-1.442		0	-4.093	**	5	-1.918	
Fin	0	-3.956	**	0	-1.989		8	-1.877		8	-0.880	
In	0	-2.598		0	-2.719		0	-3.046	*	0	-3.181	
Man	0	-3.172		0	-2.624		0	-3.529	**	0	-3.064	
Mar	0	-2.359		0	-1.441		0	-3.963	***	3	-2.056	
Te	4	-1.026		4	-3.229		4	-1.802		4	-2.454	
Ttc	0	-3.081		0	-1.013		2	-2.334		3	-1.709	
Δ Bus	0	-6.252	***	0	-5.855	***	4	-3.545	**	4	-3.108	
Δ Conn	0	-6.708	***	0	-6.763	***	4	-4.668	***	3	-4.208	
Δ Fin	0	-9.701	***	0	-9.423	***	7	-2.824		7	-2.769	
Δ In	0	-10.203	***	0	-10.144	***	0	-9.744	***	0	-9.733	
Δ Man	0	-8.347	***	0	-8.318	***	0	-8.390	***	0	-8.425	
Δ Mar	0	-8.319	***	0	-8.080	***	2	-7.600	***	2	-7.177	
Δ Te	3	-4.851	***	1	-2.935	**	3	-3.955	***	3	-3.246	
Δ Ttc	3	-6.209	***	0	-7.949	***	2	-7.917	***	2	-7.687	
Cpi	0	-0.271		0	-2.009		0	-0.430		0	-1.922	
Ppi	2	-1.577		2	-1.195		0	-0.795		0	-0.885	
Ppm	0	-1.956		0	-1.194		0	-2.048		0	-1.172	
Δ Cpi	0	-6.769	***	1	-3.245	***	0	-6.454	***	0	-6.111	***
Δ Ppi	1	-3.107		1	-3.029		0	-6.894	***	0	-6.884	***
Δ Ppm	0	-6.614	***	0	-6.540	***	1	-5.814	***	1	-5.797	***
Critical values:												
1% level		-4.134			-3.555			-3.940				
5% level		-3.494			-2.916			-3.320				
10% level		-3.176			-2.596			-3.020				

test implies stationarity, whereas testing raw data does not reject the presence of unit root. Possibly, the series may contain the seasonal unit root or structural break in the deterministic components and therefore the series will be analyzed further before making conclusion on its order of integration[35].

As discussed before choice of deterministic components affects the power of ADF unit toot test. Therefore following suggestion of Mehra (1993) I use model (15) to determine if the time trend is present in the data. If the time trend part of the data generating process valid specification of ADF test is the one with including constant as well as deterministic trend variable.

$$\Delta y_t = \alpha + \beta t + \sum_{i=1}^{k} \gamma_i \Delta y_{t-i} + \varepsilon_t \tag{15}$$

Number of lagged differences included in equation (15) is determined by Schwarz information criterion and check for presence of serial autocorrelation in residuals is performed using Ljung-Box Q-statistics. Since the series is already in natural logarithms significant t-statistics on constant indicates the series contain a linear trend. Large t-statistics on time trend would suggest the series exhibits quadratic trend. Table 2 presents the results of estimation of equation (15).

The t-statistics in Table 2 suggest that series Bus, Fin, Mar, Te and Cpi contain linear trend. The steepest slope was estimated in case of series Fin. Other series exhibit upward trends similar in magnitude. For example α equal to 0,03 implies that deterministic trend component contributes to growth in unit labor cost by 0,03% per period, what sums up to 0,09% per year. Significant negative statistics on the linear trend in equation (15) suggest that the series Bus and Te can be approximated by the concave parabola over the sample period. This implies that the growth rate of the unit labor costs is slowing down in the recent years in the Business sector and since it comprises almost 70% it is also reflected in the decreasing growth rate of the unit labor costs in the whole economy.

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[35] We should also keep in mind that ADF test suffer from low power and poor size and therefore the rejection of presence of unit root in Panel A of Table 1 can be a realization of the Type I error.

Table 2 **Determination of deterministic components of the data.**

Series	Lag length	α	α t-statistic		β	β t-statistic	
bus	1°	0.0212	2.996	**	-0.0004	-1.811	**
conn	0	0.0135	0.540		-0.0002	-0.311	
fin	8	0.0640	2.218	**	-0.0007	-0.963	
in	8	0.0057	0.247		-0.0002	-0.254	
man	0	0.0180	1.341		-0.0005	-1.217	
mar	0	0.0303	2.626	***	-0.0004	-1.046	
te	4	0.0205	4.025	***	-0.0003	-3.040	***
ttc	0	0.0195	1.087		-0.0002	-0.309	
cpi	4°	0.0196	2.290	**	-0.0002	-1.334	*
ppi	2	0.0279	1.796	**	-0.0004	-0.870	
ppm	0	0.0120	3.346	***	-0.0001	-0.833	

°lag length chosen by minimal sic exhibited serial autocorrelation in error terms, so the lag length with minimal sic among regression with no serial autocorrelation in residuals was chosen.

Critical values:		
	1% level	2.397
	5% level	1.674
	10% level	1.297

5.2.2 Unit root testing in presence of structural break

The thesis employs Perron's (1989) modification of Dickey-Fuller approach to determine whether series contain the unit root in the presence of structural break. The model allowing for most general structural break is chosen, so it can capture a change in a slope as well as a change in an intercept. Following modification of the ADF test is estimated:

$$\Delta y_t = \alpha_0 + \alpha_1 D_t(TB) + \alpha_2 t + \alpha_3 (t - TB) D_t(TB) + \gamma y_{t-1} + \sum_{i=2}^{k} \beta_i \Delta y_{t-i+1} + \varepsilon_t \qquad (16)$$

where $D_t(TB)$ is dummy variable defined as follows: $D_t(TB) = \begin{cases} 0 & t < TB \\ 1 & t \geq TB \end{cases}$.

The structural break point is treated as endogenous and recursive approach to determination of the break point is adopted. Equation (16) is estimated for $TB = k_0, k_1, ..., T$, where k_0 is chosen as $T/5$. T-statistics on γ are computed and minimum t-statistic is chosen. The lag length is determined as described in Zivot and Andrews (1990). Optimal lag length is estimated for each possible break point separately. First model (16) is estimated using 8 lagged differences. Then if β_k >1.6 and β_l <1.6 for all $l > k$, equation (16) is estimated using k lagged first differences. Results of modification of unit root tests allowing for structural break are reported in Table 3. Minimal t-statistics are compared to critical values for finite sample published in Zivot and Andrews (1990) in table 9[36].

At 5% level the hypothesis of presence of unit root can not be rejected in any of the series. The strongest evidence against the null of non-stationarity is present in case of series Ppi but it is only significant at 10% percent level and this results is not even robust to lag length selection procedure.

Table 3 Unit root test in presence of structural break – seasonally adjusted data

	Panel A Lag Length determined according to Perron (1989)			**Panel B** Lag Length determined according to SIC			
Series	**lag length**	**minimal t-statistics**	**break point**	**lag length**	**minimal t-statistics**		**break point**
bus	4	-3.639	1999:2	8	-4.173		1999:3
conn	3	-4.705	2006:1	0	-3.673		2003:2
fin	0	-4.734	2004:1	0	-3.376		1998:0
in	7	-4.500	1999:3	7	-4.113		1999:3
man	0	-3.992	1999:3	8	-4.169		2000:1
mar	7	-4.074	2006:0	5	-4.264		2005:0
te	4	-2.949	2004:0	8	-3.184		2004:2
ttc	0	-4.959	2005:0	0	-4.959		2005:0
cpi	7	-4.461	2003:1	4	-5.142		1999:3
ppi	8	-3.986	1999:3	8	-5.405	*	1999:3
ppm	7	-4.540	2004:2	7	-3.531		2005:0
Critical values:							
	1% level	-6.250					
	5%level	-5.680					
	10%level	-5.380					

Though none of the t-values in Table 3 is significant it is interesting to see which dates were estimated as most likely to be break points. All of them can be connected to specific

[36] The critical values for sample size ranging from 62 to 111 assuming normal ARMA innovations were estimated using Monte Carlo simulation.

administrative changes in economy and the reported results may indicate which series were affected by certain measures the most. For example 1993:Q3 corresponds to increase in VAT and import tariffs that affect the Business sector labor costs as well Producer prices in Industry strongly. In January 2004 flat tax rate became effective, which is had a significant impact on unit labor cost in Total economy.

5.3 Cointegration analysis – seasonally adjusted data

5.3.1 Testing for Cointegration rank-seasonally adjusted data

Since unit root tests did not reject the hypothesis of presence of unit root in any series, the next section tests for existence of cointegration relationship among unit labor costs series and CPI series. Johansen approach to determine the number of cointegration vectors[37] is used. To conduct the test described in section (3.3.2) the lag length of first differences included in the VAR model need to be determined. Following Mehra (1993) approach proposed by Sims (1980) is used. This procedure is also available in E-views. The modified likelihood ratio test sequentially test whether the lags are jointly insignificant, starting at the specified maximum lag length. In our case the maximal lag length was set to 8 for all series. If the hypothesis of joint insignificance is rejected for a particular k, then VAR model is estimated using k lags of first differences.

Another specification we need to determine is the assumption about the deterministic variables included in VAR itself as well as in cointegration relationship. Since results in Table 2 indicate that the price series contain deterministic trend specification of cointegration test where the trend is included in the data in levels but only intercept enters cointegration relationship was chosen.

[37] Since we examine cointegration in bivariate framework the maximal number of cointegration vectors is one.

To determine the number of existing cointegration relationships Johansen approach computes two statistics, namely trace statistic, λ_{trace}, and Max eigen value statistics, $\lambda_{\max}$. We look at these statistics starting with null hypothesis of $r = 0$ and then sequentially increasing r by one until we fail to reject the null. Table 4 reports the trace statistics and max eigen values statistics for the lowest r when the null hypothesis of at most r cointegration relationships can not be rejected.

Table 4 **Johansen test for cointegration rank – seasonally adjusted data**

Series	lag length		λ_{trace}	$\lambda_{\max}$	indication
(bus,cpi)	1	Ho: r=0	13.077	9.695	no cointegration
(conn,cpi)	1°	Ho: r=0	21.339	18.076	1 cointegration vector
(fin ,cpi)	1°	Ho: r=0	23.443	21.753	1 cointegration vector
(in ,cpi)	1	Ho: r=0	10.698	5.524	no cointegration
(man,cpi)	1°	Ho: r=0	12.666	7.403	no cointegration
(mar,cpi)	1	Ho: r=0	20.910	18.716	1 cointegration vector
(te,cpi)	3	Ho: r=0	20.915	18.253	1 cointegration vector
(ttc,cpi)	1	Ho: r=0	26.074	22.571	1 cointegration vector
(in ,ppi)	3	Ho: r=0	13.008	10.556	no cointegration
(man,ppm)	1	Ho: r=0	10.182	9.507	no cointegration

Critical values at 5% level

λ_{trace} 15.495

$\lambda_{\max}$ 14.265

° In case LR was the only criterion indicating the chosen lag length we choose the lag length on the basis of the majority of the criterions.

The Johansen test indicated the existence of cointegraiton relationship only in case of four series. So the unit labor costs in Fin, Mar, Te, Ttc are moving along with the overall price level measured by CPI.

5.3.2 Estimating cointegration relationship-seasonally adjusted data

To estimate the cointegration vectors we make use of Johansen estimation procedure available in the E-views software. The chosen specification accounts for presence of trend in the levels of variables.

Table 5 Cointegration vectors estimation – seasonally adjusted data

Price regressions						Wage regressions					
p	**=**	β_0	**+**	β_1	***ulc***	***ulc***	**=**	β_0	**+**	β_1	***p***
cpi	=	0.134	+	0.968	conn	conn	=	-0.138	+	1.033	cpi
cpi	=	1.240	+	0.755	fin	fin	=	-1.641	+	1.324	cpi
cpi	=	0.738	+	0.853	mar	mar	=	-0.864	+	1.172	cpi
cpi	=	-2.114	+	1.467	te	te	=	1.442	+	0.682	cpi
cpi	=	0.425	+	0.918	ttc	ttc	=	-0.463	+	1.090	cpi

Table 5 presents the results of the estimation of cointegration vectors. Price regressions represent the normalization of cointegration vector to the price level, whereas wage regression is normalization of cointegration vector to the unit labor costs variable. Since coefficient on unit labor costs are positive, higher unit labor costs correspond to higher price level.

5.3.3 Testing for weak exogenity-seasonally adjusted data

The presence of cointegration relationship between two series implies that the series are adjusting to each other so that the disequilibrium error remains stationary. However, the pure existence of cointegration does not provide information on which variable is adjusting to maintain the long run equilibrium. To determine if the price level is adjusting to unit labor cost or the other way around coefficients on test the cointegration relationship in (19) and (20) are tested to determine the weak exogenity for long run parameters β_0 and β_1. Equation (17) and (18) represent the cointegration relationships normalized to price level and unit labor costs respectively. If ulc_t is weakly exogenous in equation (17) for long run coefficients then labor cost are treated as given when determining the response of the price level and hence the cointegration relationship has causal interpretation. Parameter β_1 then estimates the long run response of price level to productivity-adjusted wages. Analogously the same applies for $1/\beta_1$ in case p_t is weakly exogenous in (12).

$$p_t = \beta_0 + \beta_1 ulc_t + u_t \tag{17}$$

$$ulc_t = -(\beta_0 / \beta_1) + (1/\beta_1) p_t + (1/\beta_1) u_t \tag{18}$$

To perform the weak exogenity test the regressions (19) and (20) are estimated and the significance of coefficients on lagged disequilibrium errors u_{t-1}.is tested. If the null hypothesis that λ_1 is different from zero can not be rejected we conclude that prices are weakly exogenous in (18). If λ_2 is zero unit labor costs are weakly exogenous in price equation (17).

$$\Delta p_t = \alpha_0 + \lambda_1 u_{t-1} + \sum_{j=1}^{k} \alpha_{1j} \Delta p_{t-j} + \varepsilon_{1t} \tag{19}$$

$$\Delta ulc_t = \delta_0 + \lambda_2 u_{t-1} + \sum_{j=1}^{k} \delta_{1j} \Delta ulc_{t-j} + \varepsilon_{2t} \tag{20}$$

Table 6 reports the results of the weak exogenity test for seasonally adjusted data. Lag length was chosen on the basis of Schwarz information criterion. Since the previous analysis determined 5 cointegration relationships, these are tested to see which variable is adjusting to maintain the long run equilibrium. Coefficient λ_2 is significant for all unit labor costs series. Therefore unit labor cost are not weakly exogenous in the price equation (17). This result implies that change in the labor costs reacts to the disequilibrium error and thereby also to the price level. The positive coefficients imply that the larger the disequilibrium error is the larger

Table 6 **Testing for weak exogenity - seasonally adjusted data**

Series	lags	λ_2	t-stat		lags	λ_1	t-stat	
(conn,cpi)	0	0.240	2.283	**	2	0.015	0.921	
(fin ,cpi)	1	0.620	4.017	***	0	0.033	1.700	**
(mar,cpi)	1	0.601	4.592	***	0	0.060	1.663	
(te,cpi)	4	0.083	1.701	**	2	-0.041	-0.634	**
(ttc,cpi)	1	0.766	4.898	***	0	0.035	1.189	

is the change in unit labor costs[38] in order to reduce the deviation from equilibrium. For all series the disequilibrium error is positive if price level is higher or unit labor costs are lower. For example, if the disequilibrium error is 0.1 point higher the change in labor costs is on average greater by slightly more than 5% in case of Market service sector.

On the other hand, insignificance of λ_1 implies that prices are weakly exogenous in some cases. Namely, for unit labor costs in Industry, Market services and Trade, transport and communication sectors. In these sectors the price level is taken as given when labor cost are adjusting to maintain the long run equilibrium. Price level does not react to size of deviations from the long run equilibrium. In case when there is some evidence for prices not being weakly exogenous the coefficient λ_1, which measure the response of the changes in price to deviation from equilibrium is small in magnitude.

5.3.4 Testing for Granger –Causality

To examine if the past values of unit labor costs carry information value for determining the current value of inflation Granger causality tests[39] are carried out. The benchmark case as described in section 3.4.1 is modified not only to determine the

[38] The disequilibrium error was obtained as $u_t = p_t - \hat{\beta}_0 - \hat{\beta}_1 ulc_t$, where the unit labor costs have negative coefficient. Therefore if the deviation is positive the change in ulc has to be larger and positive to reduce the size of deviation from long run equilibrium.

[39] Since the logic is analogous also for the case when we test if the prices Granger cause unit labor costs, we explain the procedure only for the case when we test for unit labor costs causing prices to simplify the text. The results will be provided for both cases.

significance of the past values of but also to estimate the magnitude of the effect. Moreover, cointegration relationship has to be included in the model. To estimate the magnitude of the influence of past changes in unit labor costs on inflation is important for practical interpretation of the results since the significant but small effect is of very little practical importance. To make this idea operational I follow Mehra (2000) and rearrange (21) to (22)

$$\Delta p_t = \alpha_0 + \lambda_1 u_{t-1} + \sum_{j=1}^{k} \alpha_{1j} \Delta p_{t-j} + \sum_{j=1}^{k} \alpha_{2j} \Delta ulc_{t-j} + \varepsilon_{1t} \tag{21}$$

$$\Delta p_t = \alpha_0 + \lambda_1 u_{t-1} + \sum_{j=1}^{k} (\alpha_{1j} + \alpha_{2j}) \Delta p_{t-j} + \sum_{j=1}^{k} \alpha_{2j} \Delta (ulc - p)_{t-j} + \varepsilon_{1t} \tag{22}$$

Sum of coefficients $\sum_{j=1}^{k} \alpha_{2j}$ is the estimated contribution of the changes in unit labor costs to changes in price level once the impact of the past changes in inflation has been controlled for. Therefore, the $\sum_{j=1}^{k} \alpha_{2j}$ measures the magnitude of the inflationary pressure of the past unit labor costs growth.

We can conclude that changes in unit labor cost are independent source of increase in growth of price level if $\sum_{j=1}^{k} \alpha_{2j}$ is positive and statistically different from zero. Usual F-statistics and t-statistics have conventional distributions. The hypothesis being tested can be summarized as follows:

$H_0 : \alpha_{21} = 0, \ldots, \alpha_{2k} = 0, \lambda_1 = 0$, unit labor costs do not Granger cause the prices

$H_1 : \exists \alpha_{2i} \neq 0 \; or \; \lambda_1 \neq 0$, unit labor costs do Granger cause prices

In order to analyze the causality in the opposite direction, i.e. Granger causality running from prices to unit labor costs. Analogically to model (22) the equation (23) is estimated.

$$\Delta ulc_t = \delta_0 + \lambda_2 u_{t-1} + \sum_{j=1}^{k} (\delta_{1j} + \delta_{2j}) \Delta ulc_{t-j} + \sum_{j=1}^{k} \delta_{2j} \Delta (p - ulc)_{t-j} + \varepsilon_{2t} \tag{23}$$

In case of model (23) the hypothesis are formulated as follows:

$H_0 : \delta_{21} = 0, \ldots, \delta_{2k} = 0, \lambda_2 = 0$, prices do not Granger cause unit labor costs

$H_1 : \exists \delta_{2i} \neq 0 \; or \; \lambda_2 \neq 0$, prices do Granger cause unit labor costs

The sum $\sum_{j=1}^{k} \delta_{2j}$ estimates the magnitude of the effect of past change in price level on current change in unit labor costs once we have controlled for the effect of past change in unit labor costs. The lag length in equations (22) and (23) is determined following Mehra (2000). Akaike information criterion is used to select a model and then by adding 2 final number of laggs is set. Argement behind this choice relies on higher power of the tests under the mentioned lag length selection procedure.

The results for causality test based on model (22) and (23) are reported in Table 8 and Table 7 respectively. λ_1, λ_2 are coefficients on the disequilibrium error in models (22) and (23). $F_{\lambda_1 \wedge \alpha_{2j}}$ denotes the F-statistics on the test of joint significance of the terms containing the unit labor costs in equation (22). Similarly, $F_{\lambda_2 \wedge \delta_{2j}}$ stands for F-statistics on joint significance of terms containing prices in (23). F_{Wald} is the F-statistics obtained from Wald test testing the restriction that $\sum \delta_{2j}$ and $\sum \alpha_{2j}$ are equal to zero.

By estimating equation (23) it is possible to test whether the past values of price level have impact on current change in unit labor costs series. The relevant diagnostic tests from estimation of model (23) are reported in Table 7.

Table 7 Testing for causality from prices to unit labor costs – seasonally adjusted data

Series	lags	λ_2	t-stat		$F_{\lambda_2 \wedge \delta_{2j}}$	p-value	$\sum \delta_{2j}$	F_{Wald}	p-value
(conn,cpi)	2	0.319	2.033	**	1.930	0.138	0.579	0.072	0.790
(fin ,cpi)	7	0.177	0.690		2.076	0.069	2.910	1.342	0.256
(mar,cpi)	3	0.741	4.415	***	7.076	**0.000**	0.148	0.045	0.833
(te,cpi)	6	0.089	1.234		0.822	0.576	0.183	0.622	0.436
(ttc,cpi)	3	1.032	4.290	***	5.915	**0.001**	0.506	0.277	0.601

The Granger causality was detected only in case of the series namely Mar and Ttc. However, the insignificant F_{Wald} -statistics implies that the information value is carried only in disequlibrium error. Past changes in prices do not have an effect of economic importance on changes in unit labor costs.

Table 8 reports the results from estimation of equation (21). This model allows testing for the presence of Granger causality running from unit labor costs to prices. Significant $F_{\lambda_1 \wedge \alpha_{2j}}$ -statistics indicates that there is information value in the unit labor costs series for determining the current change in price level. This is true for Fin, Mar, Ttc. On aggregate level there is no causality detected between unit labor costs and prices.

Table 8 Testing for causality from unit labor costs to prices – seasonally adjusted data

Series	lags	λ_1	t-stat		$F_{\lambda_1 \wedge \alpha_{2j}}$	p-value	$\sum \alpha_{2j}$	F_{Wald}	p-value
(cpi,conn)	4	0.379	1.809	*	0.694	0.631	-2.526	0.873	0.356
(cpi,fin)	2	0.616	3.603	***	5.762	**0.002**	-0.621	0.230	0.634
(cpi,mar)	2	0.571	3.862	***	7.801	**0.000**	-0.731	1.503	0.226
(cpi,te)	4	0.123	2.244	**	1.441	0.231	-0.133	0.491	0.488
(cpi,ttc)	4	0.937	3.158	**	3.806	**0.006**	-1.024	0.747	0.393

5.4 Cointegration analysis with raw data

Seasonal adjustment causes distortion of the cointegration inference and therefore in order to check the robustness of the previous results cointegration analysis with raw data is presented in this section. The cointegration tests are repeated with seasonally unadjusted data imposing assumption of deterministic seasonality. Therefore the models estimated in previous sections are augmented by 0-1 seasonal dummies. VECM model for raw data is described by equation (24).

$$\Delta z_t = \Gamma_1 \Delta z_{t-1} + \ldots + \Gamma_k \Delta z_{t-k} + \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} \begin{bmatrix} 1 & \beta_1 & \beta_0 \end{bmatrix} \begin{bmatrix} p_{t-1} \\ ulc_{t-1} \\ 1 \end{bmatrix} + \delta_1 c + \delta_2 (D2 - D1) + \delta_3 (D3 - D1) + \delta_4 (D4 - D1) + u_t \qquad (24)$$

where $z_t = [p_t, ulc_t]$, D_i is seasonal dummy equal to one *i*-th quarter.

Table 9 indicates the same results as Table 5 in all cases except the series In and Conn, where no long run relationship with price level is detected. So the cointegration test with seasonally unadjusted data indicates no cointegration between the unit labor costs in Industry and Construction and price level measure by consumer price index.

Table 9 Johansen test for cointegration rank – raw data

Series	lag length		λ_{trace}	$\lambda_{\max}$	indication
(bus,cpi)	3	Ho: r=0	12.704	9.457	no cointegration
(conn,cpi)	3	Ho: r=0	11.688	9.098	no cointegration
(fin ,cpi)	4	Ho: r=0	22.816	19.274	1 cointegration vector
(in ,cpi)	1	Ho: r=0	11.290	6.473	no cointegration
(man,cpi)	1	Ho: r=0	12.575	8.011	no cointegration
(mar,cpi)	1	Ho: r=0	33.271	30.830	1 cointegration vector
(te,cpi)	4	Ho: r=0	22.501	18.659	1 cointegration vector
(ttc,cpi)	2	Ho: r=0	22.235	19.621	1 cointegration vector
(in ,ppi)	1	Ho: r=0	8.995	7.167	no cointegration
(man,ppm)	1	Ho: r=0	9.332	8.584	no cointegration

Critical values at 5% level:

λ_{trace} 15.495

$\lambda_{\max}$ 14.265

Table 10 presents the results of the cointegration vectors estimation. The estimates of parameters are similar in magnitude to those reported in Table 5. It is interesting that it holds also for series Fin, which by graphical inspection does not exhibit regular seasonal pattern over the whole sample period, what casts doubt on the plausibility of assumption of deterministic seasonality.

Table 10 **Cointegration vectors estimation – raw data**

Price regressions						Wage regressions					
p	**=**	β_0	**+**	β_1	***ulc***	***ulc***	**=**	β_0	**+**	β_1	***p***
cpi	=	1.347		0.730	fin	fin	=	-1.845	+	1.370	cpi
cpi	=	0.829	+	0.834	mar	mar	=	-0.993	+	1.199	cpi
cpi	=	-2.297	+	1.512	te	te	=	1.519	+	0.661	cpi
cpi	=	0.485	+	0.908	ttc	ttc	=	-0.534	+	1.101	cpi

The results of the weak exogenity tests in the Table 11 give the same implication as those obtained using seasonally adjusted data, which are reported in Table 6. thought the selected lad length differes.

Table 11 **Testing for weak exogenity - raw data**

Series		**lags**	λ_2	**t-stat**		**lags**	λ_1	**t-stat**	
(fin ,	cpi)	8	0.579	2.395	***	0	0.035	1.599	*
(mar,	cpi)	1	1.161	5.819	***	0	0.049	1.472	*
(te,	cpi)	4	0.503	3.521	***	0	0.019	0.555	
(ttc,	cpi)	1	1.293	7.185	***	0	0.025	1.052	

The following two tables summarize the results of causality tests with raw data. These results differ from those obtained using seasonally adjusted series. Table 12 and Table 13 suggest that causality is running in both directions for Mar, Te, Ttc. In case of Fin the causality is running from unit labor costs to prices.

Table 12 **Testing for causality from prices to unit labor costs –raw data**

Series	lags	λ_2	t-stat		$F_{\lambda_2 \wedge \delta_{2j}}$	p-value	$\sum \delta_{2j}$	F_{Wald}	p-value
(fin ,cpi)	5	0.661	1.740	**	2.371	0.051	2.115	0.570	0.455
(mar,cpi)	6	1.185	2.908	***	3.542	**0.007**	-1.382	0.494	0.487
(te,cpi)	6	0.508	3.181	***	3.902	**0.004**	0.474	0.428	0.518
(ttc,cpi)	3	1.190	3.563	***	5.032	**0.002**	0.896	0.455	0.504

Although the F_{Wald} -statistics is in Table 13 is significant in case of Te. This does not imply that the unit labor cost in total economy have an independent effect on changes in price inflation once past change sin inflation has been accounted for. Negative coefficient on this effect means that the past changes in levels of inflation have greater impact that changes in unit labor costs.

Table 13 **Testing for causality from unit labor costs to prices – raw data**

Series	lags	λ_1	t-stat		$F_{\lambda_1 \wedge \alpha_{2j}}$	p-value	$\sum \alpha_{2j}$	F_{Wald}	p-value
(cpi,fin)	5	1.028	3.255	***	5.084	**0.004**	-0.471	0.065	0.801
(cpi,mar)	6	1.037	4.152	***	6.901	**0.001**	-0.207	0.050	0.824
(cpi,te)	6	0.614	4.022	***	7.630	**0.000**	-1.098	5.479	**0.024**
(cpi,ttc)	3	1.567	3.443	***	4.158	**0.003**	-0.480	0.055	0.816

For comparison no causality was detected between price level and Total economy unit labor costs using seasonally adjusted data. Since seasonal pattern Te appears to be stationary and hence imposing assumption of deterministic seasonality appear to be plausible results obtained from raw data are assumed to be more reliable. Moreover, in all cases the disequilibrium error term is significant. This result is robust across sectors for λ_1, regardless of treatment of seasonality.

Conclusion

Much of the empirical evidence suggests that unit labor cost do not Granger cause the higher inflation and therefore does not support the cost push view of inflation. Granger causality was detected only in direction from prices to unit labor costs. The previous studies were mainly concerned with US data. The thesis provides the empirical analysis of unit labor costs and price level in Slovakia covering years 1995-2008.

In order to analyzed the relationship between the unit labor cost and price level in Slovakia. data on 7 sectors of the economy were studied. First the properties of the time series were examined and the results indicate that unit labor costs series as well as price level series ca be characterized as I(1) processes. This result is robust to allowing for structural break as well seasonal adjustment.

Using Johansen procedure to testing for cointegration rank stationary long run relationship has been found between Consumer price index and unit labors in Financial services, Market service, Transport, trade and telecommunication sectors as. As before, these findings are robust to treatment of seasonality. The results indicated also the existence of long run equilibrium between overall price level and overall unit labor costs si the economy, however not between the unit labor costs in Business sector which account for almost 70% of the total economy. Indication of no long run equilibrium was found to be robust to the measure of price level case of Manufacturing and Industry sector.

Weak exogenity test suggest that prices are weakly exogenous. This result implies that unit labor costs are the variable that is adjusting to price level to maintain the long run co-movement of the variables. Even in case when prices were not indicated as weakly exogenous the effect of disequlibrium error on changes in prices has very small magnitude.

Granger causality test using raw data showed that the causality is running from unit labor costs to prices as well as in the opposite direction. However, the results with seasonally adjusted data are not in line with these implications. Both approaches agree that the information value is carried only in disequilibrium error and not in the past changes of the variables. So neither unit labor cost nor price level have an independent effect on the other variable once past changes in the left hand side variable have been included in the model.

What is an interesting result is that the unit labor costs are cointegrated with overall price level in sectors concerned with services and the bidirectional feedback works solely through the long run equilibrium relationship. Applicable policy implication of this result is that unit labor costs in services should be followed in order to improve predictions of changes in Consumer price index.

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APPENDIX 1

Figure 6 Logaritmized unit labor costs indices – raw data

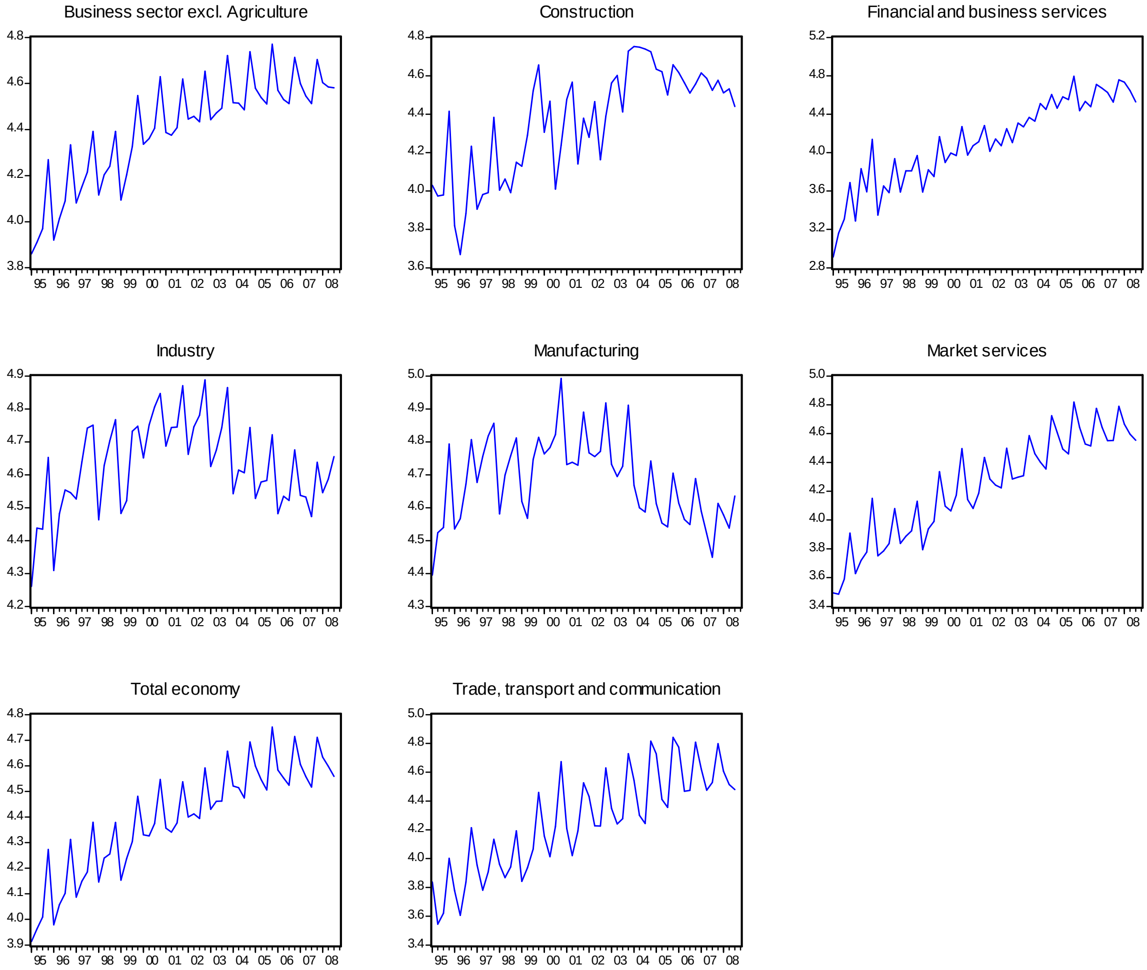

Figure 7 Logaritmized price indices – raw data

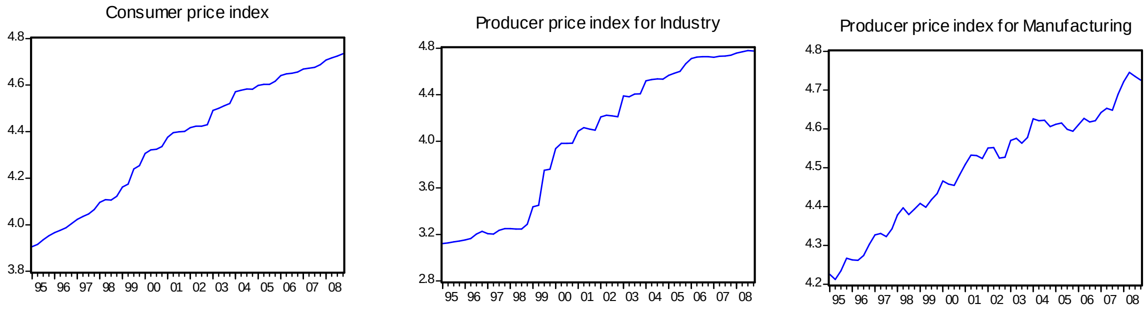

Figure 8 Logaritmized unit labor costs indices – seasonally adjusted data

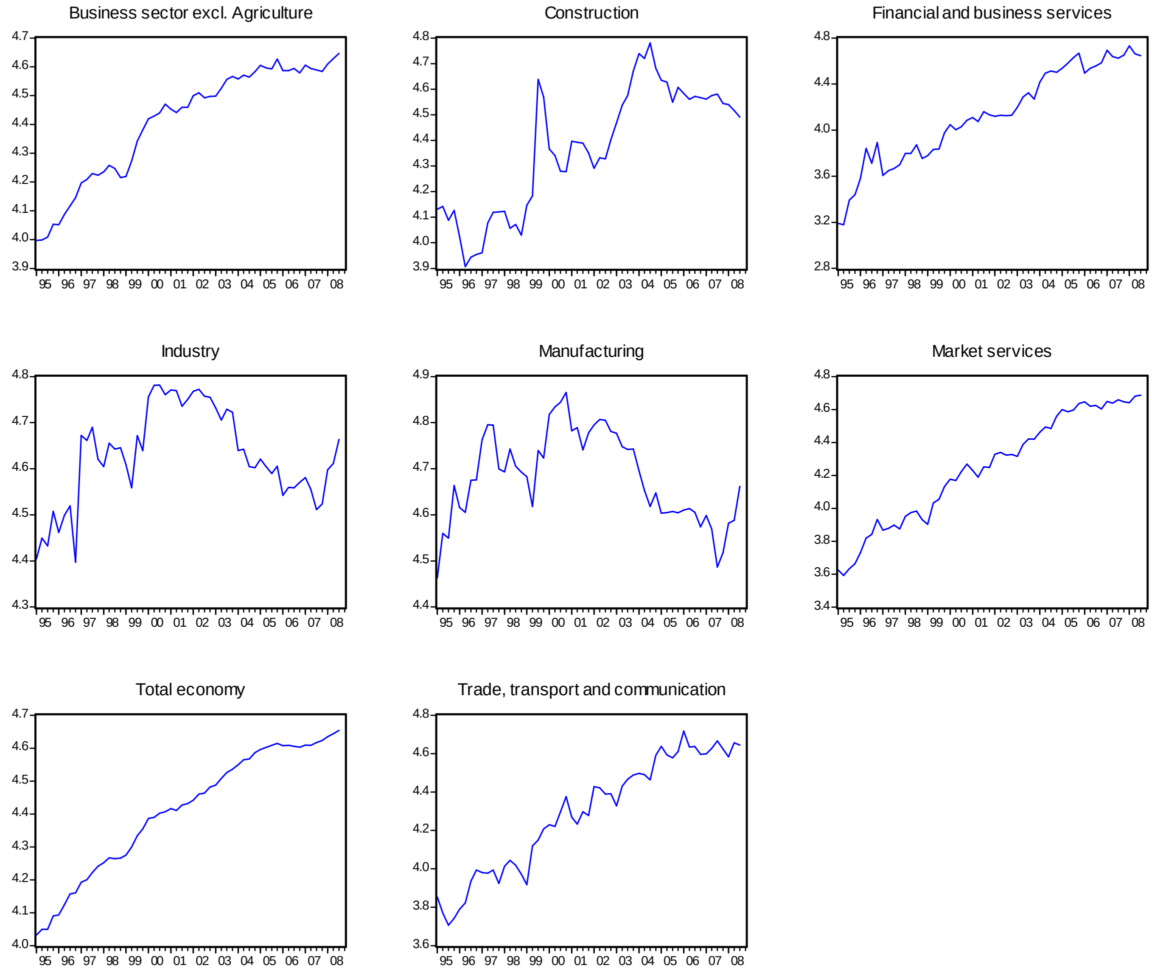

Figure 9 Logaritmized price indices – seasonally adjusted data

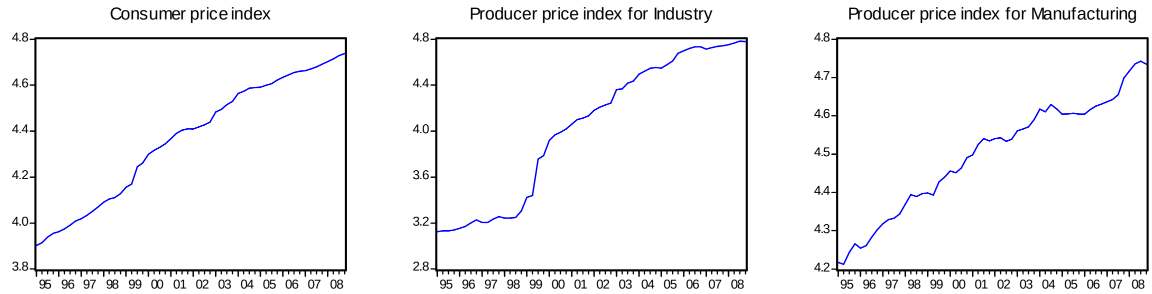

Figure 10 Year-over-year differences of unit labor costs series and CPI series

APPENDIX2

Testing for unit root at zero frequency in the presence of structural break in E-views

First truncation parameter needs to be established. The following program applies the procedure following Perron(1989) later employed by Zivot and Andrews (1990). The output of the program is the matrix containing the lag length for each break point. This matrix is the input for the program testing for structural break itself.

```
Scalar count=11                  ‘number of series
Scalar obs=56                    ‘number of observation
Scalar tb_initial=13
Scalar tb_final=50
Series t=@trend(1995)
matrix(count,56) lags_input=0
‘ Matrix lag input stores the lag parameter for each break point between tb_initial and tb_final
scalar index=0

subroutine equation (series s, scalar !tb1, scalar !row)
scalar k_index=8

series dummy_m=0
for !h=1 to obs
        if !h<!tb1 then
        dummy_m(!h)=0
        else
        dummy_m(!h)=1
        endif
next

equation eq.ls d(s) s(-1) c dummy_m t (t-!tb1)*dummy_m d(s(-1)) d(s(-2)) d(s(-3)) d(s(-4)) d(s(-5))
d(s(-6)) d(s(-7)) d(s(-8))
        while @abs(eq.@tstats(5+k_index))<1.6 and k_index>=1
        k_index=k_index-1
        wend
lags_input(!row,!tb1)=k_index
endsub

for %y lnbus_sa lnconn_sa lnfin_sa lnin_sa lnman_sa lnmar_sa lnte_sa lnttc_sa cpisa ppisa ppmsa
        index=index+1
        for !j=tb_initial to tb_final
        call equation( {%y}, !j, index)
        next
next
```

Another approach to determinantion of the lag length in the equaiton xxx is based on choosoing lag length according to SIC.

```
Scalar count=11                  'number of series
Scalar obs=56                    'number of observations
Scalar tb_initial=13
Scalar tb_final=50
Series t=@trend(1995)
Scalar index=0
matrix(count,obs) lags_input_sic=0
' Matrix lag input stores the lag parameter for each break point between tb_initial and tb_final

series dummy_m

subroutine model_selection (series s, string  %name, scalar !tb4, scalar !index)
matrix(9,2) k_{%name}_sic

for !k=0 to 8
	if !k=0 then
	equation e_{%name}.ls d(s) s(-1) c dummy t (t-!tb4)*dummy
	k_{%name}_sic(!k+1,1)=!k
	k_{%name}_sic(!k+1,2)=e_{%name}.@schwarz
	endif
	if !k=1then
	equation e_{%name}.ls d(s) s(-1) c dummy t (t-!tb4)*dummy d(s(-1))
	k_{%name}_sic(!k+1,1)=!k
	k_{%name}_sic(!k+1,2)=e_{%name}.@schwarz
	endif
	if !k=2 then
	equation e_{%name}.ls d(s) s(-1) c dummy t (t-!tb4)*dummy d(s(-1)) d(s(-2))
	k_{%name}_sic(!k+1,1)=!k
	k_{%name}_sic(!k+1,2)=e_{%name}.@schwarz
	endif
	if !k=3 then
	equation e_{%name}.ls d(s) s(-1) c dummy t (t-!tb4)*dummy d(s(-1)) d(s(-2)) d(s(-3))
	k_{%name}_sic(!k+1,1)=!k
	k_{%name}_sic(!k+1,2)=e_{%name}.@schwarz
	endif
	if !k=4 then
	equation e_{%name}.ls d(s) s(-1) c dummy t (t-!tb4)*dummy d(s(-1)) d(s(-2)) d(s(-3)) d(s(-4))
	k_{%name}_sic(!k+1,1)=!k
	k_{%name}_sic(!k+1,2)=e_{%name}.@schwarz
	endif
	if !k=5  then
	equation e_{%name}.ls d(s) s(-1) c dummy t (t-!tb4)*dummy d(s(-1)) d(s(-2)) d(s(-3)) d(s(-4))
	d(s(-5))
	k_{%name}_sic(!k+1,1)=!k
	k_{%name}_sic(!k+1,2)=e_{%name}.@schwarz
	endif
	if !k=6 then
	equation e_{%name}.ls d(s) s(-1) c dummy t (t-!tb4)*dummy  d(s(-1)) d(s(-2)) d(s(-3)) d(s(-4))
	d(s(-5)) d(s(-6))
	k_{%name}_sic(!k+1,1)=!k
	k_{%name}_sic(!k+1,2)=e_{%name}.@schwarz
	endif
	if !k=7 then
	equation e_{%name}.ls d(s) s(-1) c dummy t (t-!tb4)*dummy d(s(-1)) d(s(-2)) d(s(-3)) d(s(-4))
	d(s(-5)) d(s(-6)) d(s(-7))
	k_{%name}_sic(!k+1,1)=!k
	k_{%name}_sic(!k+1,2)=e_{%name}.@schwarz
```

```
        endif
        if !k=8 then
        equation e_{%name}.ls d(s) s(-1) c dummy t (t-!tb4)*dummy d(s(-1)) d(s(-2)) d(s(-3)) d(s(-4))
        d(s(-5)) d(s(-6)) d(s(-7)) d(s(-8))
        k_{%name}_sic(!k+1,1)=!k
        k_{%name}_sic(!k+1,2)=e_{%name}.@schwarz
        endif
next

'finding minimal sic and corresponding lag length
scalar min_sic=10

for !j=1 to 9
        if min_sic>k_{%name}_sic(!j,2) then
        min_sic=k_{%name}_sic(!j,2)
        lags_input_sic(!index, !tb4)=k_{%name}_sic(!j,1)
        endif
next
endsub
''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''‘‘‘‘‘‘‘‘‘‘‘‘‘‘‘‘‘‘‘‘‘‘‘‘‘‘‘
for !tb2=tb_initial to tb_final
         dummy_m=0
        for !h=!tb2 to obs
                dummy_m(!h)=1
        next

        call model_selection( lnbus_sa, "bus", !tb2,1)
        call model_selection (lnconn_sa , "conn",!tb2,2)
        call model_selection ( lnfin_sa ,"fin",!tb2,3)
        call model_selection ( lnin_sa ,  "in",!tb2,4)

        call model_selection (lnman_sa , "man",!tb2,5)
        call model_selection (lnmar_sa ,  "mar",!tb2,6)
        call model_selection (lnte_sa ,  "te",!tb2,7)
        call model_selection (lnttc_sa ,  "ttc",!tb2,8)

        call model_selection (cpisa ,  "cpi",!tb2,9)
        call model_selection (ppisa , "ppi",!tb2,10)
        call model_selection (ppmsa ,  "ppm",!tb2,11)
next
```

After creating the matrix of optimal lag length for each break point, the following program is realization of the procedure described in section xxx.

```
Scalar count=11                  ‘number of series
Scalar obs=56                    ‘number of observations
Scalar tb_initial=13
Scalar tb_final=50
Series t=@trend(1995)
Scalar index=0
vector(count) lag_input          ‘lag length for the break point with minimal t-statistics

for %meno bus conn fin in man mar te ttc cpi ppi ppm
        Vector(obs) t_{%meno}_tb
        Scalar min_{%meno}_tb
        Scalar final_{%meno}_tb
next

'scalar k is the “running“ lag length
'scalar tb3 denotes “running“ break point

subroutine str_break( series s , scalar !k, string %meno, scalar !tb3)

        if !k=0 then
        equation eq_{%meno}{!k}.ls d(s) s(-1) c dummy t (t-!tb3)*dummy
        t_{%meno}_tb(!tb3)= eq_{%meno}{!k}.@tstats(1)
        endif
        if !k=1then
        equation eq_{%meno}{!k}.ls d(s) s(-1) c dummy t (t-!tb3)*dummy d(s(-1))
        t_{%meno}_tb(!tb3)= eq_{%meno}{!k}.@tstats(1)
        endif
        if !k=2 then
        equation eq_{%meno}{!k}.ls d(s) s(-1) c dummy t (t-!tb3)*dummy d(s(-1)) d(s(-2))
        t_{%meno}_tb(!tb3)= eq_{%meno}{!k}.@tstats(1)
        endif
        if !k=3 then
        equation eq_{%meno}{!k}.ls d(s) s(-1) c dummy t (t-!tb3)*dummy d(s(-1)) d(s(-2)) d(s(-3))
        t_{%meno}_tb(!tb3)= eq_{%meno}{!k}.@tstats(1)
        endif
        if !k=4 then
        equation eq_{%meno}{!k}.ls d(s) s(-1) c dummy t (t-!tb3)*dummy d(s(-1)) d(s(-2)) d(s(-3))
        d(s(-4))
        t_{%meno}_tb(!tb3)= eq_{%meno}{!k}.@tstats(1)
        endif
        if !k=5 then
        equation eq_{%meno}{!k}.ls d(s) s(-1) c dummy t (t-!tb3)*dummy d(s(-1)) d(s(-2)) d(s(-3))
        d(s(-4)) d(s(-5))
        t_{%meno}_tb(!tb3)= eq_{%meno}{!k}.@tstats(1)
        endif
        if !k=6 then
        equation eq_{%meno}{!k}.ls d(s) s(-1) c dummy t (t-!tb3)*dummy d(s(-1)) d(s(-2)) d(s(-3))
        d(s(-4)) d(s(-5)) d(s(-6))
        t_{%meno}_tb(!tb3)= eq_{%meno}{!k}.@tstats(1)
        endif
        if !k=7 then
        equation eq_{%meno}{!k}.ls d(s) s(-1) c dummy t (t-!tb3)*dummy d(s(-1)) d(s(-2)) d(s(-3))
        d(s(-4)) d(s(-5)) d(s(-6)) d(s(-7))
        t_{%meno}_tb(!tb3)= eq_{%meno}{!k}.@tstats(1)
        endif
        if !k=8 then
```

```
        equation eq_{%meno}{!k}.ls d(s) s(-1) c dummy t (t-!tb3)*dummy d(s(-1)) d(s(-2)) d(s(-3))
        d(s(-4)) d(s(-5)) d(s(-6)) d(s(-7)) d(s(-8))
        t_{%meno}_tb(!tb3)= eq_{%meno}{!k}.@tstats(1)
        endif
Endsub
''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
'calling subroutine for different break points
for !tb2=tb_initial to tb_final
        dummy=0
        for !j=!tb2 to obs
                dummy(!j)=1
        next
        call str_break( lnbus_sa , lags_input(1, !tb2), "bus",!tb2)
        call str_break (lnconn_sa , lags_input(2, !tb2), "conn",!tb2)
        call str_break ( lnfin_sa , lags_input(3, !tb2), "fin",!tb2)
        call str_break ( lnin_sa , lags_input(4, !tb2), "in",!tb2)

        call str_break (lnman_sa , lags_input(5, !tb2), "man",!tb2)
        call str_break (lnmar_sa , lags_input(6, !tb2), "mar",!tb2)
        call str_break (lnte_sa , lags_input(7, !tb2), "te",!tb2)
        call str_break (lnttc_sa , lags_input(8, !tb2), "ttc",!tb2)

        call str_break (cpisa, lags_input(9, !tb2), "cpi",!tb2)
        call str_break (ppisa, lags_input(10, !tb2), "ppi",!tb2)
        call str_break (ppmsa, lags_input(11, !tb2), "ppm",!tb2)
next
''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
'searching for break point with minimal t-statistics

scalar index=0
for %meno bus conn fin in man mar te ttc cpi ppi ppm
        index=index+1
        Min_{%meno}_tb=@min(t_{%meno}_tb)
                For !i=tb_initial to tb_final
                        if min_{%meno}_tb= t_{%meno}_tb(!i) then
                        final_{%meno}_tb=!i
                        lag_input(index)=lags_input(index,!i)
                        endif
                next
next
''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''''
'produces matrix with final results for different series in rows
'first column contains the lag length////second minimal t-statistics////third break point
'fourth year of the break point////fifth quarter of the break point
matrix(count,5) str_output

for !r=1 to count
        str_output(!r, 1)=lag_input(!r)
next
scalar i=1
for %y bus conn fin in man mar te ttc cpi ppi ppm
        str_output(i, 2)=min_{%y}_tb
        str_output(i, 3)=final_{%y}_tb
        i=i+1
next
i=1
for !r=1 to 11
        str_output(!r, 4)=@floor(str_output(!r,3)/4)+1995
        str_output(!r, 5)=str_output(!r,3)-@floor(str_output(!r,3)/4)*4
next
```