Cointegration analysis of the monthly time-series relationship between retail sales and average wages in Croatia

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Abstract

A dynamic econometric model of Croatian monthly retail sales and wages is estimated through testing sequential model reduction validity. Such an approach aims at developing well-performing and interpretable dynamic relationships as data-description models. In addition to the model in levels a more economically interpretable error correction model was estimated enabling direct evaluation of the short-run impact of wage change to retail change as well as the periodic adjustment to the long-run equilibrium. It was established that, both in the short-run and in the long-run, retail sales respond to wages thus forming a stable dynamic relationship.

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1. Introduction

The dynamic relationship between retail sales and wages in transitional economies has not been systematically investigated, mainly due to problems relating to the availability and quality of transitional time series data. These data problems include the existence of grey economy, short data series (for post-Communist period), and problematic quality of macroeconomic data because of the measurement error and changes in the systems of national accounts. The existing literature on econometric modelling of transitional consumption and income data is scarce and based exclusively on micro (household) data that are available only for several countries (e.g., Denizer et al. 2000). Macroeconomic studies analysing dynamic co-movements of retail sales and wages in transitional countries, using time-series and econometric techniques, are still not present in the literature.

The effect of movements in wages on retail sales, however, carries substantial policy importance requiring this relationship to be empirically investigated. The additional importance of the data on wages lies in the fact that wages can be determined, to large degree (particularly public-sector wages), by the government in negotiations with the labour unions and facilitation of enterprise-level wage negotiations. In Croatia, the government had further set guidelines for state-owned enterprises on wage policy (mainly limiting growth of wages and inducing temporary wage freeze in the late 1999). The remaining movements in wages are due to productivity growth and other stochastic economic factors. It is clear, however, that the government can influence the growth of average wages, most notably in the public sector. Therefore, if average wages were found to affect retail sales, this would provide basis for fiscal policy measures aimed at increasing or decreasing consumption spending. Moreover, the growth of average wages has been among central issues in the Croatian consultations with the IMF. In the recent years, the IMF recommended against stimulating growth in wages[2] and even suggested government's intervention toward decreasing average wages, linking growth in average wages with unemployment and recession. However, the relationship between growth in average wages and consumption spending (e.g., retail sales) has not been seriously

[2] The recommendations related primarily on public-sector wages. However, due to the large public sector, these recommendations have strong bearing on the overall economy, and private-sector wages are strongly correlated with the public-sector ones.

investigated. Likewise, no serious attempt has been made to empirically model the effect of movements in average wages on retail sales in Croatia.

The aim of this paper is to develop a dynamic econometric model of retail sales and wages (average over private and public sectors) using Croatian monthly time series data from the IMF statistics for the 1994-2000 period (Dorsey et al., 1995; Elkan and Temprano-Arroyo, 1998; Artus and Kapur, 2000; Elkan and Maggi, 2000). The modelling approach is empirical, using the general-to-specific methodology (see Hendry, 1983; 1987; 1995). The analysis in this paper recognises the specific characteristics of transitional economies and properties of transitional time series data, specifically it emphasises model building and estimation of relatively simple dynamic relationships not through testing specific theoretical hypothesis (i.e., specification testing), but through extensive mis-specification and diagnostic testing of sequential model reduction validity. Such an approach aims at developing econometrically well-performing and economically interpretable stable dynamic relationships as data-description models. This type of modelling is modest in scope but essential in transitional data analysis where there is neither strong theory (of transitional processes) nor a substantial body of previous research to draw upon.

On the theory side, note that a stable relationship between income and consumption in general, and thus wages and retail sales in particular, is not unanimously accepted in the literature. The well known rational expectation permanent income hypotheses (Hall, 1978), for example, negates such relationship altogether but that is frequently rejected in empirical studies (e.g., Sargant, 1978; Flavin, 1981). More recent evidence against Hall's hypothesis is given in Mansen and McAleer (2000; 2001).[3]

The following econometric analysis models the effect of average wages on retail sales taking into account data issues such as non-stationarity and (monthly) seasonality, deriving estimation equations from the unknown joint density of the analysed variables by a series of marginalisations, rather then estimating coefficients of a theoretically postulated model. The econometric analysis in this paper starts with detailed descriptive data analysis followed by step-by-step derivation of the estimation equation through marginalisation of unobserved components in the general

[3] Though our immediate purpose is not to test the permanent income hypothesis with Croatian data, note that a finding of a significant relationship between change in retail sales and change in wages

model. These steps were outlined in detail to make all reductions and simplifications tractable and to emphasis the general-to-specific approach. The methodological issues and approaches are of high importance in transitional data analysis. The theoretical foundations and previous studies in this field are scarce and provide little reliable guidance in the modelling process. Therefore, the empirically-grounded general-to-specific methodology together with strong focus on statistical model evaluation and diagnostics is essential in this case.

The paper is organised in three parts. In the first part, the descriptive properties of the data are analysed. It is found that both series are non-stationary, i.e., $I(1)$, requiring cointegration analysis. In the second part, the estimation equation is derived through feasible marginalisations of the general joint density function. In the third part, a general autoregressive distributed lag model (ADL) is estimated using seasonally unadjusted data and a cointegration relationship between retail sales and average wages is established. An error-correction model (ECM) is further estimated, simultaneously modelling short and long run and establishing a significant, both short- and long-run effect of wages on retail sales. Additionally, an annual-difference model is estimated, following Davidson et al. (1978), which showed low ability for capturing seasonality which indicated necessity for the use of seasonal dummies.

2. The data

The 1994-2000 Croatian time series data for monthly retail sales and monthly wages are available in the IMF statistics (Country Reports series), namely Artus and Kapur (2000), Dorsey et al. (1995), Elkan and Maggi (2000), and Elkan and Temprano-Arroyo (1998). Interest rates data on average interest rate on deposits (nominal, unfixed) are also available as a monthly time series from the same sources.

According to the available household data (Croatian Household Budget Surveys 1998-2000, 2002)[4], retail sales comprise nearly 60% of the consumption of households, while the remaining 40% goes on housing expenditures, energy, credit

would indicate excess sensitivity of consumption and thus violate the permanent income hypothesis of Hall (1978).

[4] The survey methodology is based on the EU Household Budget Survey and recommendations for harmonisation 1997, No. 361 of the European Union, used by EUROSTAT for harmonisation of methodologies among the EU Member States.

repayments, etc. Wages comprise about 70% of the total personal disposable income with remaining 30% being property royalties, unemployment benefits, scholarships, etc. The data on average wages include bonuses, sick pay, and meal allowances, coming from monthly surveys covering approximately 70% of the labour force from all major industrial categories. According to the IMF reports, the data on labour income (wages) excludes persons employed in trade and crafts, contract workers, farmers, and military and police workers (IMF Staff Country Report No. 00/7, 2000). All data series are in US dollars, measured in constant prices. The retail price series is expressed in thousands of $US.

Fig. 1 shows time series plots of (log) levels (retail) and differences (Dretail) of the monthly retail sales together with their Gaussian kernel density estimates (for more details see Silverman, 1986; Hendry and Doornik, 1999). Levels show regular seasonal pattern with steady growth and approximately normal (Gaussian) distribution, while first-differencing apparently removed trending behaviour. The time-plot of 12th differences (D12retail) is also shown, following the "annual change" reasoning of Davidson et al. (1978)[5]. However, annual differencing introduced hectic behaviour in the series causing induced non-stationarity and non-normality.

Plots of levels, first and 12th differences of (log) monthly wages and their accompanying density estimates are shown in the bottom part of Fig. 2. The trending behaviour of the levels is even more notable then in the case of retail sales, though seasonal pattern is less expressive. The first-differencing not only removed the trend but also normalised the distribution. Again, 12th differences appear non-stationary and non-normally distributed.

Fig. 1. (about here)

To further graphically describe the data, Fig. 2 shows autocorrelation function (ACF) and partial autocorrelation function (PACF) plots for the levels, first- and 12th-differences of retail sales and wages. Levels of both variables show long memory decay in the ACF combined with a large first spike in the PACF indicating an $I(1)$ non-stationary processes. Subsequently, first-differences appear stationary, i.e., $I(0)$, while 12th-differences show again clear $I(1)$ pattern.

Table 1 reports the descriptive statistics and formal normality tests for each variable. Both exact and asymptotic X^2 statistics are reported (see D'Augustino, 1970; Bowman and Shenton, 1975; Shenton and Bowman, 1977; Doornik and Hansen, 1994; Hendry and Doornik, 1999).

Fig. 2. (about here)

As already indicative from the density plots, we cannot reject the hypotheses that the levels of retail sales and first differences of wages are normally distributed. First differences of retail sales and levels and 12th-differences of wages, on the other hand, significantly deviate from normality, while normality of the 12th-difference of retail sales can be rejected only on the 9% level.

Table 1
(about here)

In subsequent testing for unit roots, i.e., non-stationarity, in the data we first note several issues related to likely effects of aggregation. Our data is disaggregated in comparison to the series used in most of the literature on consumption research in two respects. First, we use monthly instead of quarterly or annual data (temporal disaggregation) and we use retail sales and wages as components of total personal consumption and income (disaggregation across variables).

Using monthly instead of quarterly (or annual) data, for the same time span, increases the frequency of observations three times. This increase in data frequency can be viewed as time-disaggregation of quarterly series. The opposite effect would occur by aggregating monthly into quarterly series. The crucial point is that time aggregation itself might have substantial effect on econometric inference and data analysis. In particular, aggregation might reduce the power of some unit root tests and thus make stationary series, i.e. $I(0)$, appear non-stationary, i.e., $I(1)$. This could result in inappropriate differencing or a finding of deceptive cointegration relationships.

Time disaggregation (i.e. the use of higher frequency series) thus might affect the power of the unit root tests, though there is some Monte Carlo evidence suggesting

[5] Annual differencing might remove seasonality from the data that would make the use of seasonal dummies unnecessary thus preserving degrees of freedom.

that the power of these tests depend less on data frequency and more on the span of the data (see Shiller and Perron, 1985 and Perron, 1989a). However, data frequency seems to have stronger effect on tests applied to "flow" data such as consumption or GDP (Maddala and Kim, 1998). Specifically, unit root tests using flow data appear to have higher power at higher data frequencies (Choi, 1992). Ng (1995) further showed that power of these tests depends both on frequency and on the span of data. In particular, the power tends to raise with the increase in frequency unless the span is simultaneously shortened. A reanalysis by Choi and Chung (1995) of the Shiller and Perron (1985) and Perron (1989a) findings confirmed the conclusions of Choi (1992) and Ng (1995) in the case of augmented Dickey-Fuller (ADF) tests (Dickey and Fuller, 1979). Namely, they found that increase in frequency alone can increase the ADF test power in finite samples, which however might not hold in the case of Phillips-Perron (PP) unit root tests whose finite sample power against the null of unit root appears to be less affected by the data frequency (see also Blough, 1992).

Aggregation over variables such as in the systems of national accounts can also have important statistical implications. An example of a variable aggregated by summation over other variables is personal consumption (i.e. retail purchases, expenditures on housing, energy, credit repayment, etc.). Gourieroux and Monfort (1997) show that, theoretically, the presence of strong temporal correlations can be the outcome of aggregation through introduction or temporal smoothing of the aggregated series if these were correlated among each other. In the matter of fact, it can be shown that the aggregation of a short-memory series can generate a long-memory stationary series or even nonstationary series (Gourieroux and Monfort, 1997). The variables entering the definition of total consumption are highly likely to be strongly inter-correlated, thus their aggregate is more likely to appear to have stronger temporal dependence then the processes of variables comprising it taken individually. Therefore, from the statistical point of view, the use of disaggregated data (e.g., components of total consumption and income) is likely to be more justified then the use of sums of possibly intercorrelated components.

Of relevance for unit-root testing in our case is to note that the above arguments support the conjecture that unit root tests (e.g. Dickey-Fuller) will have higher power against the null for less aggregated (temporal and across variables) data then for standard quarterly consumption-income data (Perron, 1991; see also Working, 1960).

The empirical testing for the order of integration is undertaken by adopting the augmented Dickey-Fuller (ADF) test to seasonally unadjusted monthly data by assuming deterministic seasonality. One way to proceed is to first regress:

$$y_t = \alpha_0 + \sum_{i=1}^{11} \alpha_i d_i + \hat{\varepsilon}_t \tag{1}$$

and then use the regression residuals to estimate and ADF test of the form (see Enders, 1995):

$$\Delta\hat{\varepsilon}_t = \gamma\hat{\varepsilon}_{t-1} + \sum_{i=2}^{s} \delta_i \Delta\hat{\varepsilon}_{t-i+1} + u_t \,. \tag{2}$$

Dickey, Bell and Miller (1986) show that the distribution of γ in (2) is not affected by the presence of the dummy variables. Alternatively, we can estimate:

$$\Delta y_t = \alpha + (\beta - 1) y_{t-1} + \sum_{i=1}^{s} \gamma_i \Delta y_{i-i} + \sum_{i=1}^{m} \delta_i d_i + \mu t + \varepsilon_t \,. \tag{3}$$

Allowing for deterministic trend in the DGP of retail sales (r_t) and wages (w_t) variables (Fig. 1. and 2.) a general ADF specification with constant, trend and seasonal dummies is initially estimated (Table 2). Estimation of Eq. (3) and testing for the significance of μ found that the time trend is insignificant and was thus dropped from the ADF equation.

Table 2
(about here)

Recalculating the ADF tests without the time trend, keeping seasonal dummies,[6] we find that both retail and wages variables have a unit root (Table 2). The highest significant lag for the ADF test on retail was 9th ($p = 0.014$) and 12 for wages ($p =$

[6] While a seasonal pattern is easily visible in the time plot of retail sales series (Fig. 1), it is less noticeable for the wages (Fig. 2). However, regressing each variable on the 12 seasonals (i.e., constant and 11 dummies) finds significant seasonality in most months, thus seasonals were retained in the assumed DGP for the ADF tests. Note that the presence of deterministic (dummy) variables in this case does not change the distribution of the ADF test statistic.

0.013), with the accompanying ADF t-values of – 2.347 and – 0.561, respectively (5% critical value is 3.474 for the case with the constant and seasonals included).

The statistical characteristics of the individual series thus imply that both retail sales and wages can be described by a random walk with drift. Furthermore, both series exhibit seasonal pattern in their DGPs, where deterministic seasonality is particularly strongly present in the retail series. The notable seasonality is most likely caused by the large share of agriculture and tourism in the GDP. Growth over time is thus easily noticeable, though deterministic time trend was not significant in Eq. (3).

3. Econometric methodology

Empirical research and econometric modelling of consumption and income is rather scarce in transitional economies. In the case of analysing the aggregate time series relationships between retail sales and wages, little or no previous empirical evidence exists. Needless to say, any reliance on, or search for, a well developed economic theory in the existing literature that would fully explain consumption function in transitional economies is bound to be a fruitless quest. At best, we are able to sketch some elements of the general consumption theory and possible implications for the relationship between retail sales and wages. That could, to some degree, facilitate model building and interpretation of the results. Thus, while there still might be some place for disagreements regarding econometric methodology insofar "theory-models" and "empirical-models" are concerned (see Hendry, 1987; 1995), in the case of modelling the yet un-modelled data of transitional economies, the primacy and final arbitrage of empirical evidence and econometric testing is unquestionable.

A satisfactory econometric model in this case should satisfy a number of statistical and economic criteria. The finally chosen model should be *congruent* with the data in the sense of Hendry and Richard (1982) and Hendry (1987; 1995). Congruency requires *innovation error process* (see Sargan, 1964; Hendry, 1995 and Davidson, 2000), at least *weak exogeneity* of the regressors (in single equation models) in the sense of Engle et al. (1983), *parameter constancy* (Chow, 1960; Tanaka, 1983; Pesaran et al., 1985), *economic interpretability*, and *encompassing* of the alternative (rival) models (Hendry, 1975; Hendry and Anderson, 1977; Davidson et al., 1978; Hendry and Richard, 1982; 1989; Mizon, 1984; Mizon and Richard, 1986).

To derive the initial (general) empirical estimation equation given the above considerations, let $income_t = W_t + h_t$ where W_t stands for wages and h_t presents income coming from sources other then wages (property royalties, unemployment benefits, scholarships etc.). Similarly, let $consumption_t = R_t + \tau_t$ where R_t are retail sales and τ_t stands for other consumption (expenditures on housing, energy, credits repayment, etc.). Suppose that the static (or long-run equilibrium) relationship between consumption and income could be linearly approximated as

$$consumption = \delta + \phi \cdot income + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma} \tag{9}$$

where $\mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}$, presents all other possible variables (presently ignoring deterministic components such as trend and seasonals). Then, using the above definitions we have:

$$(R + \tau) = \delta + \phi(W + h) + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma} \Rightarrow R = \delta + \phi W + \phi h - \tau + \mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}$$

thus, a stochastic version would be $R_t = \delta + \phi W_t + \phi h_t - \tau_t + \mathbf{z}_t^{\mathrm{T}}\boldsymbol{\gamma} + \varepsilon_t$, $\varepsilon_t \sim$ i.i.d. With $\{h_t, \tau_t, \mathbf{z}_t^{\mathrm{T}}\boldsymbol{\gamma}\}$ unobserved we could estimate only

$$R_t = \delta' + \phi' W_t + u_t \tag{10}$$

where $u_t = \phi h_t - \tau_t + \mathbf{z}_t^{\mathrm{T}}\boldsymbol{\gamma} + \varepsilon_t$ and $\delta' \approx \delta$ and $\phi' \approx \phi$ if $u_t \sim$ i.i.d., however note that $\varepsilon_t \sim$ i.i.d. does not imply that $u_t \sim$ i.i.d.

Estimation of Eq. (10) would require fulfilment of several preconditions to be valid (see Hendry and Richard, 1982 and Hendry, 1987; 1995). We first define the joint density for the (unknown) data generating process (DGP) as

$$D(X_T^1 | X_0; \theta_T^1) = D(R_T^1, W_T^1, \mathbf{Z}_T^1 | R_0, W_0, \mathbf{Z}_0; \psi_T^1), \tag{11}$$

where $D(\cdot)$ denotes the joint density of all variables in the model, R_T and W_T are sample data on retail sales and wages, respectively, Z_T includes data on all other variables (e.g., unobserved or unavailable, irrelevant, etc.), and $\boldsymbol{\psi}_T$ is the vector of parameters. Let $\{r_t, s_t\}$ be the observable variables of interests (i.e., logarithms of retail sales and wages) and let $\mathbf{z}_t \equiv \{\tau_t, h_t : \mathbf{v}_t\}$ where $\mathbf{v}_t$ is the vector of unobservable and/or irrelevant variables. In order to obtain innovation errors we can condition on the past values of all variables by forming the joint likelihood

$$\prod_{t=1}^{T} D(r_t, w_t, \mathbf{z}_t | R_{t-1}, W_{t-1}, \mathbf{Z}_{t-1}; \phi_t). \tag{12}$$

To marginalise the unwanted variables out of the model we rewrite the joint density as a product of a conditional density of the variables we wish to exclude given the ones we wish to model and the marginal density for the later

$$\prod_{t=1}^{T} D(\tau_t, h_t, \mathbf{v}_t | r_t, w_t, R_{t-1}, W_{t-1}, \mathbf{Z}_{t-1}; \delta_1) D(r_t, w_t | R_{t-1}, W_{t-1}, \mathbf{Z}_{t-1}; \delta_2). \tag{13}$$

Given our parameters of interest are contained in the vector $\boldsymbol{\delta}_2$ only, we marginalised out the first factor in Eq. (12) containing the current values of h_t and τ_t (the unobserved variables) and the current values of $\mathbf{v}_t$ hence retaining

$$\prod_{t=1}^{T} D(r_t, w_t | R_{t-1}, W_{t-1}, \mathbf{Z}_{t-1}; \delta_2). \tag{14}$$

The history (i.e., past information) of the variables that we marginalised out of the model can be omitted too given these variables do not Granger-cause any of the included variables (Granger, 1969), i.e.,

$$\prod_{t=1}^{T} D(r_t, w_t | R_{t-1}, W_{t-1}, \mathbf{Z}_0; \gamma_t) \tag{15}$$

which is required to assure that no information loss occurred in this last marginalisation. However, as it is not possible to test for Granger non-causality in respect to the unobserved variables, Eq. (15) must be justified by economic arguments. Again, ignoring $\mathbf{z}^{\mathrm{T}}\boldsymbol{\gamma}$, it is necessary that neither h_t nor τ_t Granger-cause retail and wages. This requires that the past non-retail consumption expenditures (e.g., housing, energy, credits repayment, etc.) and non-wage income wages (property royalties, unemployment benefits, scholarships etc.) do not affect current retail sales and wages. This argument is likely to hold for the later case as wages are not under direct control of the employees, while in the first case we note that the non-retail consumption expenditures are comprised of primarily less variable and transitory components whose dynamic effect is likely to be lost on the aggregated level.

Next, factoring the joint density into the conditional density for retail given wages and marginal density for wages gives

$$\prod_{t=1}^{T} D(r_t | w_t, R_{t-1}, W_{t-1}, \mathbf{Z}_0; \phi_1) D(w_t | R_{t-1}, W_{t-1}, \mathbf{Z}_0; \phi_2). \qquad (16)$$

This last marginalisation would allow us to model only the conditional density thus ignoring the marginal density for the wages. This, in turn, justifies the use of a single equation model requiring weak exogeneity of w_t (see Engle et al., 1983; Ericsson, 1992 and Hendry, 1995). Note that this issue only concerns the possibility of a contemporaneous feedback from wages to retail and that a single-equation version of an unrestricted VAR (including only lagged values) would avoid this problem (Sims, 1980). Formally, weak exogeneity requires that in Eq. (16) all parameters of interest are obtainable only from ϕ_1 and that ϕ_1 and ϕ_2 impose no mutual restrictions (are "variation free"), i.e., for $\phi_1 \in \mathbf{\Phi}_1$ and $\phi_2 \in \mathbf{\Phi}_2$ it should be that $(\phi_1 : \phi_2) \in \mathbf{\Phi}_1 \times \mathbf{\Phi}_2$. From the practical point of view, monthly wages are endogenous to monthly retail sales due to short time interval (one month). Namely, the public sector wages are determined by the government, hence they are controlled and thus exogenous, while private sector wages are more likely to respond to retail movements, though not so quickly. Note that weak exogeneity status largely depends on the time units used: for annual macroeconomic variables hardly any variable is truly exogenous, while for higher-frequency data (e.g., monthly) cross-variable feedbacks are likely to be small (see Sargan, 1964 for some early empirical evidence in modelling marginal density of private wages).

Finally, given we have a relatively small sample with monthly observations we *a priori* need to truncate the maximum lag-length in the operational version of our model. The degrees-of-freedom considerations are important because too generous ADL formulations (in term of lag-length) would eat up too many degrees of freedom making all estimated parameters appear insignificant. Thus, too general models would not allow progressive simplification, as any simplification could be considered acceptable in such case. To cover possible annual dynamics and further allow for the first differences of the annual differences we truncate the lag-length to 13. Additionally some distributional assumptions must be made by replacing $D(\cdot)$ with a specific density $F(\cdot)$. Thus, the likelihood equation (16) becomes

$$\prod_{t=1}^{T} F(r_t | w_t, R_{t-1}^{t-13}, W_{t-1}^{t-13}; \beta_1) \qquad (17)$$

where, the estimation equation is derived from the conditional expectation, i.e.,

$$E(r_t | w_t, R_{t-1}^{t-13}, W_{t-1}^{t-13}) = \alpha_0 + \sum_{t=1}^{T} \beta_i r_{t-i} + \sum_{t=0}^{T} \delta_i w_{t-i} + \sum_{i=1}^{11} \phi_i D_i \ . \tag{18}$$

The linear specification in Eq. (18) allows for the use of seasonally unadjusted data thus incorporating deterministic seasonal components D_i (deterministic trend can also be included). The issue of modelling seasonality vs. seasonal adjustment is important in case of short transitional time series, as seasonal adjustment techniques (e.g., X-12 ARIMA) are gaining unjustified popularity due to apparent conservation of the degrees of freedom due to exclusion of seasonal dummy variables. Such seasonal adjustment might cause serious distortion of the results indicating either spurious relations or failing to capture the truly existing ones (see Hecq, 1998 for recent evidence on this matter). Finally, to conjecture an approximate form for $F(\cdot)$ note that a stochastic version of Eq. (18) can be written as

$$\varepsilon_t = r_t - \alpha_0 - \sum_{t=1}^{T} \beta_i r_{t-i} - \sum_{t=0}^{T} \delta_i w_{t-i} - \sum_{i=1}^{11} \phi_i D_i \ . \tag{19}$$

However, making distributional assumptions about ε_t such as $\varepsilon_t \sim \mathrm{IN}(0, \sigma^2)$ where the error is independent from the regressors, i.e., $D(w_t, \varepsilon_t) = D(w_t) \cdot D(\varepsilon_t)$[7] evokes Leamer's "axiom of correct specification" (Leamer, 1978) which cannot be generally valid for empirical model-discovery purposes. Instead, it follows from Eq. (19) that ε_t should be considered a derived process whose density depends on the joint density of the model's variables, i.e., $F(\cdot)$, which should be approximated or discovered in the process of empirical modelling (see Hendry, 1980; 1983; 1987; 1995 and Gilbert, 1986).[8] Testing for normality (Bowman and Shenton, 1975; D'Agostino, 1970; Doornik and Hansen, 1994; Shenton and Bowman, 1977) and homoscedasticity of the $\{\varepsilon_t\}$ process (White, 1980) as well as for parameter stability (Chow, 1960; Hansen, 1992; Tanaka, 1983) are among practically fesable ways of evaluating model validity.

[7] Note that in our model wages are the only contemporaneous regressor.

[8] However, note that marginal normality of all random variables in the model would imply normal error process.

5. Estimation results

Having derived a sufficiently general estimation equation, we now proceed with empirical estimation. Given we already found that $r_t \sim I(1)$ and $w_t \sim I(1)$, we first test for cointegration (see Engle and Yeo, 1991a; 1991b, Engle et al. 1991, Engle and Granger, 1987; 1991, Hendry, 1991; Banerjee et al., 1993; Hamilton, 1994). Having only two $I(1)$ variables the estimation proceeds in the single-equation framework (Engle and Granger, 1987).[9] Estimating the following equation in levels by OLS

$$r_t = \alpha + \beta w_t + \varepsilon_t \tag{20}$$

produces the long-run estimates (standard errors in parentheses)

$$r_t = \underset{(0.31)}{9.67} + \underset{(0.04)}{0.67} w_t + \varepsilon_t \tag{21}$$

$R^2 = 0.767$ $\sigma = 0.116$ DW = 0.92.

Applying the ADF test on the residuals from Eq. (21) to test whether $\phi = 0$ in

$$\Delta\hat{\varepsilon}_t = \phi\hat{\varepsilon}_{t-1} + \sum_{t=1}^{p-1} \delta_i \Delta\hat{\varepsilon}_{t-i} + u_t \tag{22}$$

and retaining only significant lags of the first-differences, produces the following result

$$\Delta\varepsilon_t = -\underset{(0.09)}{0.38}\varepsilon_{t-1} + \underset{(0.09)}{0.26}\Delta\varepsilon_{t-2} + \underset{(0.08)}{0.19}\Delta\varepsilon_{t-3} + \underset{(0.07)}{0.18}\Delta\varepsilon_{t-4} + \underset{(0.06)}{0.11}\Delta\varepsilon_{t-5} + \underset{(0.06)}{0.87}\Delta\varepsilon_{t-12} + u_t \tag{23}$$

$R^2 = 0.829$ $\sigma = 0.0511$ DW = 2.26.

The calculated t-value for ϕ coefficient is -4.256 which exceeds the cointegration ADF critical value of -3.5267 (MacKinnon, 1991), thus the null of unit root can be rejected indicating that r_t and w_t are cointegrated in levels in Eq. (21). Note that since both variables are in logs, this indicates that the income-consumption ratio (i.e., proxied by wages and retail), that is the average propensity to consume (APC), is stationary so that APC in the long run converges to a constant (see also Sarantis and

[9] See Engle and Yeo (1991a, 1991b), Engle, Granger and Hallman (1991). Banerjee et al. (1993) is a more comprehensive reference, while Enders (1995), Harris (1995) and Price (1998) provide less technical overviews of the cointegration analysis.

Stewart, 1999 for the evidence from OECD countries and review of main literature on this topic).

Having found a cointegration relationship between retail sales and wages, a general autoregressive distributive lag (ADL) model based on Eq. (18) is estimated. Initially, we include 13 lags of each variable allowing for annual-differencing and differencing of annual-differences (see Davidson et al., 1978). In addition, a set of 11 monthly dummies (D_i) are included in the general formulation.[10] We call the initial general model M_1 which is defined as

$$M_1\text{:}\ r_t = \alpha_0 + \sum_{i=1}^{13} \beta_i r_{t-i} + \sum_{i=0}^{13} \delta_i w_{t-i} + \sum_{i=1}^{11} \phi_i D_i + \varepsilon_t \ . \tag{24}$$

Following the general-to-specific reduction process (see Hendry, 1995 and Hendry and Doornik, 1999), tests for joint significance of each lag lead to simplified formulation which retained only 7 lags and the set of seasonal dummies (model M_2)

$$M_2\text{:}\ r_t = \alpha_0 + \sum_{i=1}^{7} \beta_i r_{t-i} + \sum_{i=0}^{7} \delta_i w_{t-i} + \sum_{i=1}^{11} \phi_i D_i + \varepsilon_t \ . \tag{25}$$

By further reductions and dropping of insignificant terms the following model was obtained

$$M_3\text{:}\ r_t = \alpha_0 + \sum_{i=1}^{3} \beta_i r_{t-i} + \delta_0 w_t + \delta_2 w_{t-2} + \delta_6 w_{t-6} + \delta_7 w_{t-7} + \sum_{i=1}^{11} \phi_i D_i + \varepsilon_t \,. \tag{26}$$

Omitting detailed estimates from each reduction stage, the summary model statistics for the progressively reduced sequence from M_1 to M_3 are reported in Table 4. It can be seen that M_1 and M_2 have similar regression standard errors, but the Schwarz criterion favours strongly M_3 primarily due to its parsimony and highest degrees of freedom.

Table 4
(about here)

[10] Davidson et al. (1978) argued that annual differencing might remove most of the seasonality making seasonal dummies unnecessary. However, if the further model reduction process is to lead to an error correction (ECM) specification, which might retain some variables in levels, annual-differencing will not remove the seasonal pattern (Hendry and von Ungern-Sternberg, 1981).

Model reduction encompassing tests (see Mizon, 1984; Mizon and Richard, 1986; Hendry, 1995 and Hendry and Doornik, 1999) are given in the bottom part of Table 4. Reductions from M_1 through M_2 to the final model, M_3, caused no significant difference in the statistical properties of the model, thus making the reductions acceptable or "F-acceptable" using Gilbert's (1986) terminology.

The full estimates from the model M_3 are given in Table 5. Aside of the constant term all coefficients have significant t-values. The heteroscedasticity-consistent standard errors (HCSE) are similar to the OLS standard errors indicating residual homoscedasticity (White, 1980).

Table 5
(about here)

So far we have not included the interest rate (R_t) in the estimated models due to degrees of freedom limitation. Instead, the effect of interest rate including its lagged values was tested via a Lagrange multiplier (LM) test for omitted variables. The test statistic for the effect of omitting R, R_{t-1}, R_{t-2}, R_{t-3}, R_{t-4}, R_{t-5}, R_{t-6}, and R_{t-7} of 1.327 was insignificant (p-value = 0.252). Similar results were obtained by including lags up to 13^{th}. This suggests that interest rate has no (linear) effect on retail sales and thus no explanatory power in the estimated ADL model.

Fig. 3. (about here)

Graphical model diagnostics for the final model (M_3) are shown in Fig. 3. Model fit appears good with white noise, normally distributed residuals (Fig. 3c,e,f). The last 12 values in the estimation sample were used for testing the forecasting performance. The forecasts are shown with the accompanying 95% confidence bounds in Fig. 3.d. All forecasted values fall within the confidence bounds (see also Table 6). The model was estimated with recursive least squares which enabled dynamic analysis and parameter constancy tests. Recursive estimates of the model coefficients are shown in Fig. 4 and indicate satisfactory parameter constancy across the entire sample with narrow confidence bounds.

Table 6
(about here)

Calculated forecast Chow test of 1.029 ($p = 0.442$) indicates no significant discrepancy between actual and forecasted values further supporting stability of the model's coefficients.

Fig. 4. (about here)

Further parameter constancy diagnostics are shown graphically in Fig. 5. Fig. 5a shows a plot of 1-step residuals with $0 \pm 2\sigma$ bounds showing no notable model deficiencies, though a slightly higher value for 1997(12) might be observed. The recursively computed 1-step Chow tests (Fig. 5b) scaled by their critical values at the 5% significance level indicate possible problems in 1996(7) and, as suggestive by the 1-step residual plot, in 1997(12). *N* decreasing and *N* increasing recursive Chow tests (scaled by their critical values) are plotted in Fig. 5b,d showing no parameter inconstancy from t to T.

Fig. 5. (about here)

The analysis of the lag structure and significance tests for individual variables (including all lags) was used as primary selection criteria. The ADL formulation in levels is not generally orthogonal, thus the presence of multicolinearity among the regressors might make model reduction based on case-wise deletion of variables with low t-ratios misleading. Consequently, greater emphases were placed on the lag structure analysis then on individual t-ratios in the model reduction process.

The results of the lag structure analysis for the final model (M_3) and the tests for (total) significance of each variable are given in Table 7. Both sets of tests indicate high significance of all included variables and lags.

Table 7
(about here)

Finally, the mis-specification tests for model M_3 (Table 8) found no significant autocorrelation in the residuals up to fifth lag (AR 1-5), nor any autoregressive conditional heteroscedasticity (ARCH) effect in the residuals. Residuals appear approximately normally distributed. Heteroscedasticity (X_i^2) and general functional form mis-specification (RESET) tests also don't reject.

Commencing from the estimated ADL model, Eq. (26), we calculate the static long-run solution which gives the following result

$$\begin{aligned} r_t = {} & \underset{(0.90)}{10.52} + \underset{(0.12)}{0.63}w_t - \underset{(0.79)}{1.74}D_2 - \underset{(0.36)}{0.82}D_3 + \underset{(0.38)}{0.57}D_4 - \underset{(0.23)}{0.48}D_5 - \underset{(0.36)}{0.83}D_6 \\ & - \underset{(0.30)}{0.65}D_7 - \underset{(0.16)}{0.27}D_8 - \underset{(0.24)}{0.44}D_9 - \underset{(0.31)}{0.62}D_{10} - \underset{(0.23)}{0.43}D_{11} - \underset{(0.46)}{0.98}D_{12} + u_t \end{aligned} \tag{27}$$

Wald test $X^2(12) = 37.972 \quad p = 0.000$.

The long run coefficients of all variables including seasonals are significant and well determined with the joint significance Wald test of 37.972 confirming the existence of a stabile long run solution. Using seasonally unadjusted data, in Eq. (27) we allowed the deterministic seasonal components to enter the long-run (equilibrium) solution. Alternatively, wishing to use the long-run solution in an error correction model that exclude deterministic seasonals from the cointegration space, we additionally estimated a simple ADL(13) model without seasonal dummies, which solved for the long-run produced

$$r_t = \underset{(0.79)}{9.15} + \underset{(0.10)}{0.73}w_t + u_t \tag{28}$$

Wald test $X^2(1) = 55.477 \quad p = 0.000$.

The ADL(13) long-run solution turns out to be highly significant with very large value of the Wald test. Note that the elasticity of wages increased 14% in Eq. (28) as compared to Eq. (27) and its standard error decreased for 16%. Comparing Eq. (28) with the Eq. (21) which is estimated in levels, we find approximately the same value of intercept with 8% larger income elasticity.

We next estimate an error correction (ECM) model using the above calculated long-run equilibrium solution as an ECM term. The estimated ECM model aims to capture 1-step short-term monthly dynamics combined with an adjustment to the long-run equilibrium effect. The deterministic seasonal components were left outside of the ECM term (thus seasonal dummies do not enter the cointegration space) and only first-differences of retail sales and wages were used together with a set of seasonal dummies (which was sequentially reduced, retaining only significant seasonals).

While in general, and ECM model is merely a re-parameterisation of the accompanying ADL model, thus not its restricted version, the model we estimate here is a slightly restricted version of the estimated ADL model (M_3) aimed at capturing simplest short-term dynamics only. The estimation produced the following result

$$\begin{aligned}\Delta r_t = & \underset{(0.23)}{0.52}\Delta w_t - \underset{(0.04)}{0.11}(r_{t-1} - 9.15 - 0.73 w_{t-1}) \\ & - \underset{(0.02)}{0.31}D_2 + \underset{(0.02)}{0.12}D_3 + \underset{(0.02)}{0.05}D_4 + \underset{(0.02)}{0.07}D_7 - \underset{(0.02)}{0.08}D_{11} + \underset{(0.02)}{0.15}D_{12} + u_t\end{aligned} \tag{29}$$

$R^2 = 0.911 \quad \sigma = 0.037 \quad DW = 2.29.$

The individual coefficients appear well determined with significant t-ratios and the Durbin-Watson statistic is not too far from 2, though it is possible that some dynamics might have been omitted. Eq. (29) shows a 0.52 elasticity of a monthly change in wages in respect to monthly change in retail sales. Furthermore, the monthly adjustment towards the long-run equilibrium is approximately 11%. These results indicate statistically significant and stable dynamic relationship between retail sales and wages. Therefore, wage policy can influence consumption. Specifically, increase in average wages will increase retail sales in the short run with a (negative) adjustment to the long-run equilibrium. Note also that such results violate the random walk hypothesis of Hall (1978) finding the response of changes in retail sales overly sensitive to changes in wages.

Additional testing of the estimated ECM model for mis-specification (Table 9) reveals possible heteroscedasticity and general functional form mis-specification which is likely due to omitted more complex dynamics. However, the use of HSCE instead of OLS standard errors did not change the significance of the t-ratios on any of the coefficients.

Graphical evaluation of the estimated ECM model (Fig. 6) indicated apparently good fit and acceptable forecasting performance in the last 12 months of the sample period (Fig. 6d). Model residuals also appear white noise and approximately normally distributed (Fig. 6c,e,f).

Fig. 6. Goodness-of-fit and graphical evaluation for the ECM model

Finally, parameter constancy tests reveal that the recursively estimated coefficients of Δw_t and of the ECM term are relatively constant over the sample period with 1-step residuals within 95% confidence bounds (with possible exception in January of 1997). The 1-step Chow test (Fig. 7d) indicates a possible break point in 1997(1) which is confirmed by the *N* increasing Chow test (Fig. 7f). The apparent break is likely to be a consequence of omitted dynamics since the full ADL model did not display any likely structural breaks at the beginning of 1997 (Fig. 4).

Fig. 7. (about here)

So far it was found that annual-differences are of little help in the estimated models. Neither 12th order lags appeared significant nor did 12th differences properly behaved statistically (see Table 1). Nevertheless, we additionally estimate a monthly replication of the quarterly Davidson et al. (1978) general (nesting) annual-difference model (we call it here M_4 which used levels as well as differences and a vector of seasonal dummies ($\mathbf{d}^T\boldsymbol{\psi}$)

$$M_4: r_t = \underset{(1.40)}{3.83} + \underset{(0.08)}{0.81}r_{t-1} - \underset{(0.10)}{0.20}r_{t-12} + \underset{(0.09)}{0.22}w_t + \underset{(0.07)}{0.07}w_{t-12} + \underset{(0.27)}{0.36}\Delta w_t + \underset{(0.20)}{0.13}\Delta w_{t-12} + \mathbf{d}^T\boldsymbol{\psi} + u_t \tag{30}$$

$R^2 = 0.975$ $\sigma = 0.0357$ $DW = 2.23$.

Dropping insignificant terms and re-estimating the reduced model produced

$$M_5: r_t = \underset{(1.22)}{4.22} + \underset{(0.09)}{0.73}r_{t-1} - \underset{(0.07)}{0.16}r_{t-12} + \underset{(0.09)}{0.30}w_t + \mathbf{d}^T\boldsymbol{\psi} + u_t \tag{31}$$

$R^2 = 0.964$ $\sigma = 0.0346$ $DW = 2.11$

Eq. (30) incorporates annual-differencing and potentially allows dropping seasonal dummies. However, its reduced version, Eq. (31), no longer allows for annual-differences of wages thus seasonality cannot be removed simply by annual-differencing as suggested by Davidson et al. (1978) in their quarterly case. Additionally, we test for the encompassing between models M_3 and M_4 finding that M_3 encompasses M_4 while M_4 does not encompass M_3 (Table 10).

The estimated long-run solution in both specifications (with and without seasonal dummies) showed a stable long-run relationship between retail sales and wages.

Furthermore, the elasticity of wages is below one and statistically significant, specifically a change in retail sales responds to change in wages with approximately 11% monthly adjustment to the long run.

6. Conclusions

In this paper a dynamic econometric model of Croatian monthly retail sales and wages was developed and estimated using seasonally unadjusted data. The main findings indicate a stable long-run relationship between retail sales and average wages which were found to be individually nonstationary but jointly cointegrated. Following a series of several reductions, starting from a fairly general autoregressive distributed lag formulation, a specific dynamic model was estimated in levels. The model selection criteria emphasised extensive diagnostic and mis-specification testing, lag-structure analysis and graphical evaluation, requiring the final model to be data congruent with innovation error process and to have constant parameters. In addition, the selected specific model was required to encompass alternative rival models and show good forecasting performance in the last sample year. In addition, a more economically interpretable error correction model was estimated enabling direct evaluation of the short-run impact of wage change to retail change as well as the periodic adjustment to the long-run equilibrium. The estimated error correction model was a somewhat constrained version of the previously estimated model in levels, but it has nevertheless showed relatively good performance in terms of evaluation testing, parameter constancy and forecasting performance. Most importantly, it was established that, both in the short-run and in the long-run, retail sales do respond to wages thus forming a stable dynamic relationship. Additional testing for the effects of nominal, unfixed average interest rates on deposits with the omitted variables LM test showed no evidence of significant influence on retail sales.

The results from this paper showed that it is possible to estimate simple dynamic econometric models with typical data from transitional countries further developing one of the first empirical econometric models with data of this kind. Moreover, it was shown that statistically well-performing models can be estimated with the newly available transitional time series data. Because of the lack of previous empirical studies and strong theoretical foundations, econometric modelling with transitional data places special emphasis on the general-to-specific econometric methodology and extensive statistical post-estimation testing and model evaluation.

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Table 1
Normality tests and descriptive statistics

	r_t	Δr_t	$\Delta_{12} r_t$	w_t	Δw_t	$\Delta_{12} w_t$
μ (mean)	14.892	0.009	0.112	7.819	0.010	0.164
σ (std. dev.)	0.200	0.119	0.103	0.216	0.022	0.108
$\sigma_{(T-1)}$:	0.202	0.119	0.104	0.218	0.022	0.108
Skewness	0.176	− 1.497	− 0.192	− 0.109	0.013	1.794
Kurtosis	− 0.366	3.080	− 0.975	− 1.338	− 0.642	1.940
Minimum	14.480	− 0.394	− 0.096	7.452	− 0.035	0.051
Maximum	15.354	0.216	0.302	8.161	0.060	0.470
$X^2(2)$	0.556	26.467	4.924	11.148	0.781	138.670
X^2 p-value	0.756	0.000	0.085	0.004	0.676	0.000
a.s. X^2	0.778	55.362	3.297	5.516	1.243	49.916

a.s. = asymptotic value

Table 2
Unit-root tests

Variable	Constant, trend and seasonals included[a]						Constant and seasonals included[b]					
	t-ADF*	β (y_{t-1})	σ_β	t-value[c]	t-prob	F-prob	t-ADF	β (y_{t-1})	σ_β	t-value[c]	t-prob	F-prob
r_{t-13}	– 2.245	0.646	0.0357	1.016	0.315	–	0.565	1.018	0.037	0.266	0.791	–
r_{t-12}	– 2.037	0.692	0.0357	– 0.451	0.654	0.315	0.549	1.017	0.037	– 1.330	0.190	0.791
r_{t-11}	– 2.380	0.668	0.0354	1.004	0.320	0.543	0.617	1.019	0.037	0.156	0.876	0.413
r_{t-10}	– 2.178	0.710	0.0354	– 0.063	0.949	0.532	0.611	1.019	0.037	– 0.919	0.362	0.612
r_{t-9}	– 2.347	0.707	0.0350	2.540	0.014	0.694	0.714	1.022	0.037	1.795	0.078	0.621
r_{t-8}	– 1.660	0.789	0.0369	0.045	0.964	0.157	0.618	1.019	0.037	– 0.547	0.586	0.345
r_{t-7}	– 1.744	0.790	0.0366	0.673	0.503	0.233	0.621	1.019	0.037	0.052	0.958	0.428
r_{t-6}	– 1.623	0.816	0.0364	1.096	0.278	0.285	0.629	1.019	0.037	0.547	0.586	0.537
r_{t-5}	– 1.342	0.855	0.0364	– 0.669	0.506	0.283	0.697	1.021	0.037	– 1.266	0.211	0.607
r_{t-4}	– 1.718	0.829	0.0362	– 0.682	0.497	0.330	0.484	1.014	0.037	– 1.468	0.147	0.548
r_{t-3}	– 2.195	0.801	0.0360	0.815	0.418	0.375	0.193	1.005	0.037	0.097	0.922	0.454
r_{t-2}	– 2.046	0.826	0.0359	1.381	0.172	0.404	0.213	1.006	0.037	0.831	0.409	0.534
r_{t-1}	– 1.717	0.858	0.0362	– 1.690	0.096	0.351	0.341	1.009	0.037	– 2.246	0.028	0.558
r_t	– 2.343	0.814	0.0368	–	–	0.259	– 0.108	0.996	0.038	–	–	0.307
w_{t-13}	– 0.674	0.929	0.0137	– 0.967	0.338	–	– 2.035	0.978	0.013	– 0.933	0.355	–
w_{t-12}	– 0.561	0.941	0.0137	– 2.570	0.013	0.338	– 1.862	0.981	0.013	– 2.633	0.011	0.355
w_{t-11}	– 0.663	0.927	0.0145	– 0.504	0.616	0.031	– 1.205	0.987	0.014	– 0.592	0.556	0.027
w_{t-10}	– 0.733	0.920	0.0144	– 0.044	0.964	0.064	– 1.101	0.989	0.014	– 0.079	0.936	0.055
w_{t-9}	– 0.743	0.920	0.0143	– 0.485	0.629	0.118	– 1.123	0.989	0.014	– 0.518	0.606	0.104
w_{t-8}	– 0.762	0.919	0.0141	0.711	0.480	0.176	– 1.047	0.990	0.014	0.637	0.529	0.155
w_{t-7}	– 0.694	0.927	0.0141	– 1.780	0.081	0.223	– 1.263	0.988	0.014	– 1.886	0.065	0.205
w_{t-6}	– 0.882	0.906	0.0144	– 0.653	0.516	0.132	– 0.869	0.992	0.014	– 0.850	0.399	0.109
w_{t-5}	– 1.037	0.892	0.0143	0.459	0.648	0.167	– 0.714	0.993	0.014	0.286	0.775	0.129
w_{t-4}	– 0.983	0.900	0.0142	– 1.668	0.101	0.215	– 0.806	0.993	0.014	– 1.892	0.063	0.175
w_{t-3}	– 1.290	0.869	0.0144	2.950	0.004	0.150	– 0.448	0.996	0.014	2.803	0.007	0.100
w_{t-2}	– 0.928	0.899	0.0154	– 2.919	0.005	0.025	– 1.034	0.990	0.015	– 3.395	0.001	0.019
w_{t-1}	– 1.844	0.798	0.0164	– 2.470	0.016	0.004	– 0.650	0.993	0.016	– 3.508	0.001	0.001
w_t	– 3.064	0.684	0.0172	–	–	0.001	– 0.637	0.993	0.018	–	–	0.000

[a] Critical values: 5% = – 3474; 1% = – 4.093.
[b] Critical values: 5% = – 2.903; 1% = – 3.525.
[c] Values of t statistics for the coefficient γ of Δy_{t-i} in Eq. (3).

Table 4

Comparative model evaluation results

Model statistics

Model	T	k	*d.f.*	RSS	σ	Schwarz
M_3	71	19	52	0.054	0.032	– 6.031
M_2	71	27	44	0.051	0.034	– 5.603
M_1	71	39	32	0.033	0.032	– 5.318

Model reduction (encompassing) tests

Model reduction	*d.f.*	Test statistic	p-value
Model $1 \rightarrow 2$:	F(12, 32)	1.455	0.192
Model $1 \rightarrow 3$:	F(20, 32)	1.006	0.480
Model $2 \rightarrow 3$:	F(8, 44)	0.296	0.963

Table 5

OLS estimates from model M_3

Variable	Coefficient	σ	t-value	t-prob	HCSE	Part. R^2
α_0	1.313	0.724	1.812	0.075	0.782	0.053
r_{t-1}	0.812	0.119	6.776	0.000	0.122	0.441
r_{t-2}	0.430	0.142	3.013	0.003	0.132	0.135
r_{t-3}	– 0.364	0.130	– 2.794	0.007	0.112	0.118
w_t	0.332	0.132	2.514	0.014	0.162	0.098
w_{t-2}	– 0.424	0.150	– 2.821	0.006	0.161	0.120
w_{t-6}	0.543	0.204	2.655	0.010	0.210	0.108
w_{t-7}	– 0.373	0.180	– 2.072	0.042	0.188	0.068
D_2	– 0.385	0.031	– 12.054	0.000	0.043	0.714
D_3	– 0.169	0.034	– 4.927	0.000	0.033	0.295
D_4	0.137	0.046	2.953	0.004	0.041	0.130
D_5	– 0.081	0.037	– 2.178	0.033	0.036	0.075
D_6	– 0.163	0.035	– 4.567	0.000	0.034	0.264
D_7	– 0.129	0.026	– 4.843	0.000	0.026	0.288
D_8	– 0.052	0.024	– 2.137	0.036	0.024	0.073
D_9	– 0.095	0.026	– 3.659	0.000	0.027	0.187
D_{10}	– 0.137	0.025	– 5.376	0.000	0.028	0.332
D_{11}	– 0.096	0.021	– 4.374	0.000	0.023	0.248
D_{12}	– 0.207	0.021	– 9.486	0.000	0.023	0.608

$R^2 = 0.980$; $F(18,58) = 154.19$ ($p = 0.000$); $\sigma = 0.034$; DW = 1.90

Table 6

Analysis of 1-step forecasts for model M_3

Date	Actual	Forecast	A – F	Forecast SE	t-value
2000(1)	14.790	14.834	– 0.043	0.039	– 1.114
2000(2)	14.872	14.857	0.014	0.038	0.380
2000(3)	15.013	15.001	0.011	0.038	0.309
2000(4)	15.099	15.056	0.043	0.036	1.170
2000(5)	15.161	15.114	0.047	0.038	1.249
2000(6)	15.211	15.167	0.043	0.038	1.144
2000(7)	15.290	15.228	0.061	0.038	1.590
2000(8)	15.317	15.275	0.042	0.039	1.060
2000(9)	15.269	15.295	– 0.025	0.040	– 0.633
2000(10)	15.258	15.240	0.018	0.040	0.460
2000(11)	15.191	15.156	0.034	0.040	0.848
2000(12)	15.354	15.290	0.063	0.038	1.645

Table 7

Tests on the significance of variables

Variable	F-test	Value	Probability
α_0	F(1, 41)	5.159	0.028
r_t	F(3, 41)	31.122	0.000
w_t	F(4, 41)	5.670	0.001
D_2	F(1, 41)	118.370	0.000
D_3	F(1, 41)	24.526	0.000
D_4	F(1, 41)	5.880	0.019
D_5	F(1, 41)	6.404	0.015
D_6	F(1, 41)	22.956	0.000
D_7	F(1, 41)	25.283	0.000
D_8	F(1, 41)	5.269	0.026
D_9	F(1, 41)	11.179	0.001
D_{10}	F(1, 41)	24.350	0.000
D_{11}	F(1, 41)	14.568	0.000
D_{12}	F(1, 41)	73.821	0.000

Table 8
Tests on the significance of lags

Lag	F-test	Value	Probability
1	F(1,41)	29.961	0.000
2	F(2,41)	6.515	0.003
3	F(1,41)	6.898	0.012
6	F(1,41)	8.529	0.005
7	F(1,41)	6.053	0.018
1-7	F(6,41)	15.799	0.000
2-7	F(5,41)	3.710	0.007
3-7	F(3,41)	3.824	0.016
4-7	F(2,41)	4.508	0.017
5-7	F(2,41)	4.508	0.017
6-7	F(2,41)	4.508	0.017
7-7	F(1,41)	6.053	0.018

Table 9
Mis-specification and encompassing tests

ADL model			
Test	degrees-of-freedom	Test statistic	p-value
AR 1-5	F(5,36)	1.070	0.392
ARCH 5	F(5,31)	0.752	0.590
Normality	$X^2(2)$	1.393	0.498
X_i^2	F(25,15)	0.870	0.632
RESET	F(1,40)	0.054	0.816
ECM model			
Test	degrees-of-freedom	Test statistic	p-value
AR 1-5	F(5,58)	2.371	0.090
ARCH 5	F(5,53)	1.161	0.340
Normality	$X^2(2)$	1.937	0.379
X_i^2	F(10,52)	2.092	0.041
RESET	F(1,62)	4.477	0.038

Table 10
Encompassing test statistics

$M_3\,\varepsilon\,M_4$	Form	Test	Form	$M_4\,\varepsilon\,M_3$
– 2.579	N(0,1)	Cox	N(0,1)	– 9.816
2.110	N(0,1)	Ericsson IV	N(0,1)	7.304
4.259	$X^2(4)$	Sargan	$X^2(5)$	13.663
1.070	F(4,48)	Joint model	F(5,48)	3.334
p = 0.381				p = 0.012

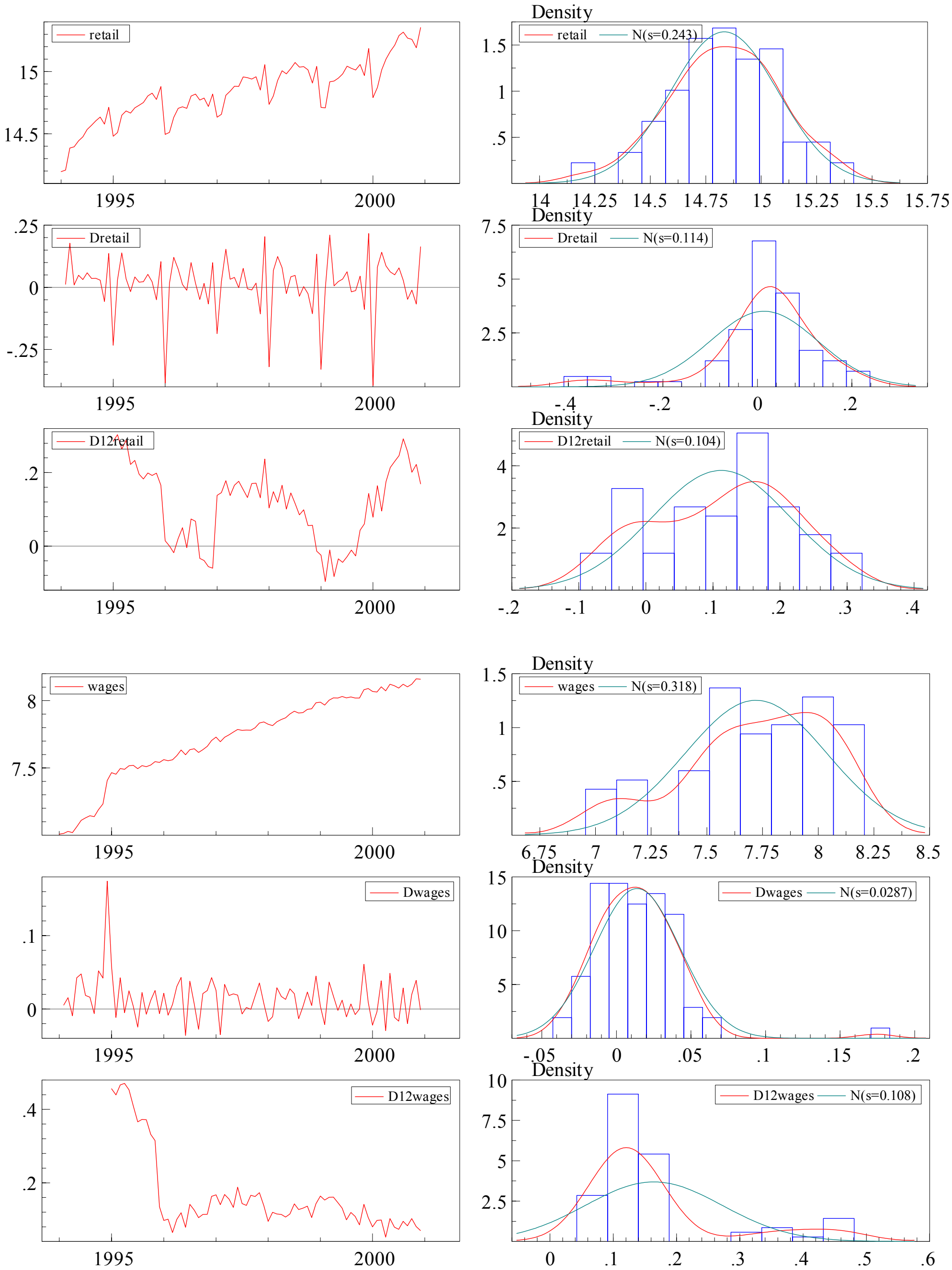

Fig. 1. Retail sales and average wages (logarithms), their first and 12th differences and empirical distributions (Gaussian kernel estimate).

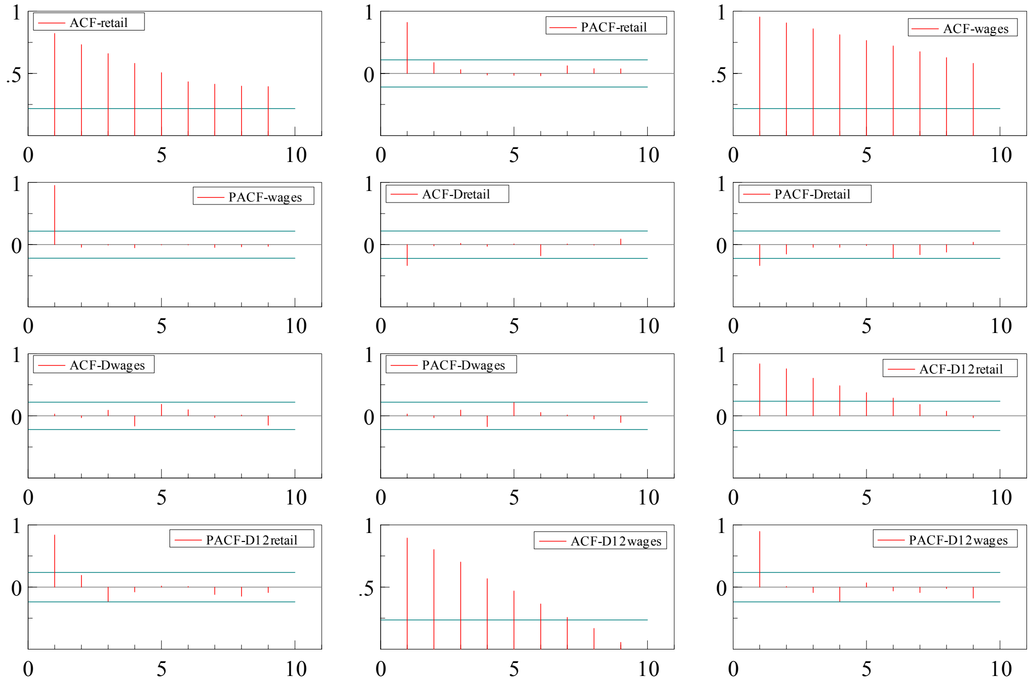

Fig. 2. Autocorrelation (ACF) and partial autocorrelation (PACF) functions for retail sales and wages and for their first- and 12th-differences

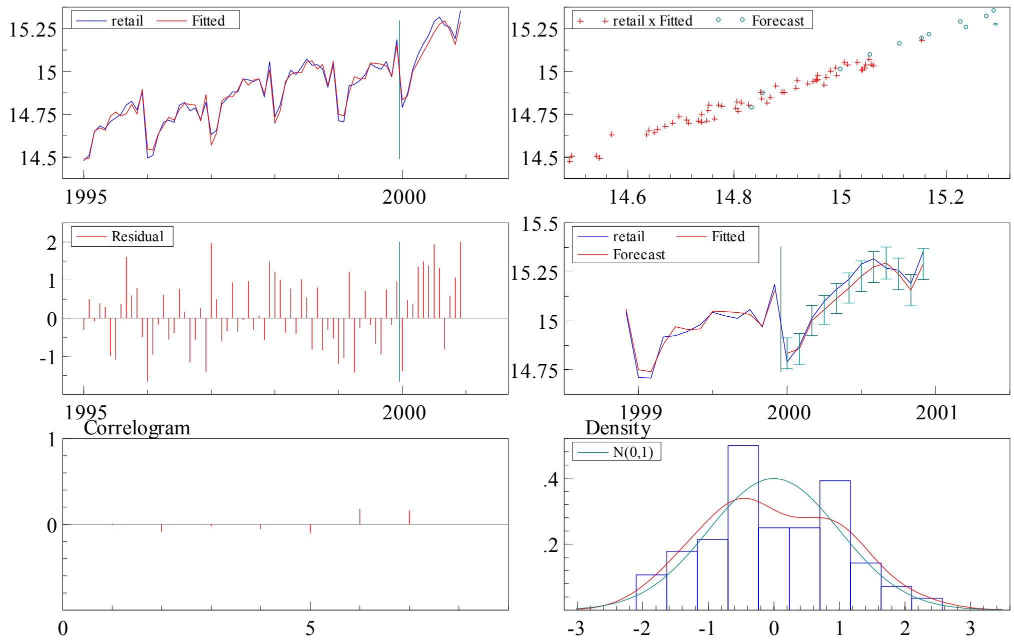

Fig. 3. Goodness-of-fit and graphical evaluation of model M_3

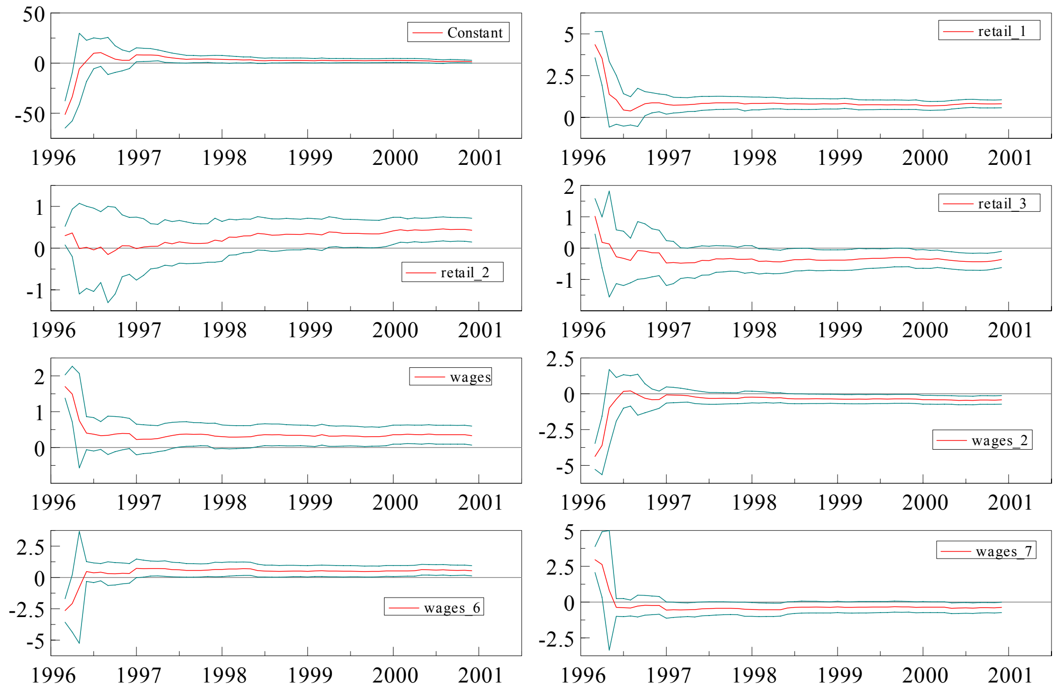

Fig. 4. Recursive estimates of coefficients in model M_3

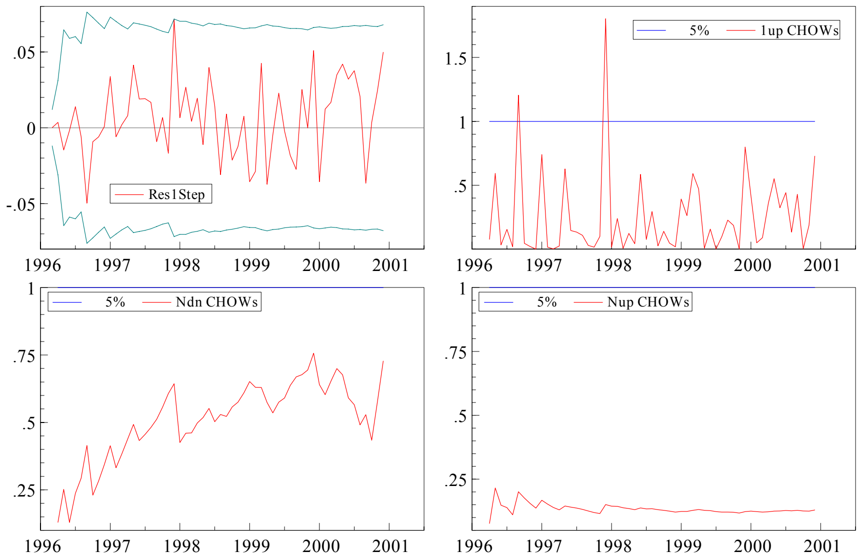

Fig. 5. Recursive constancy statistics for model M_3

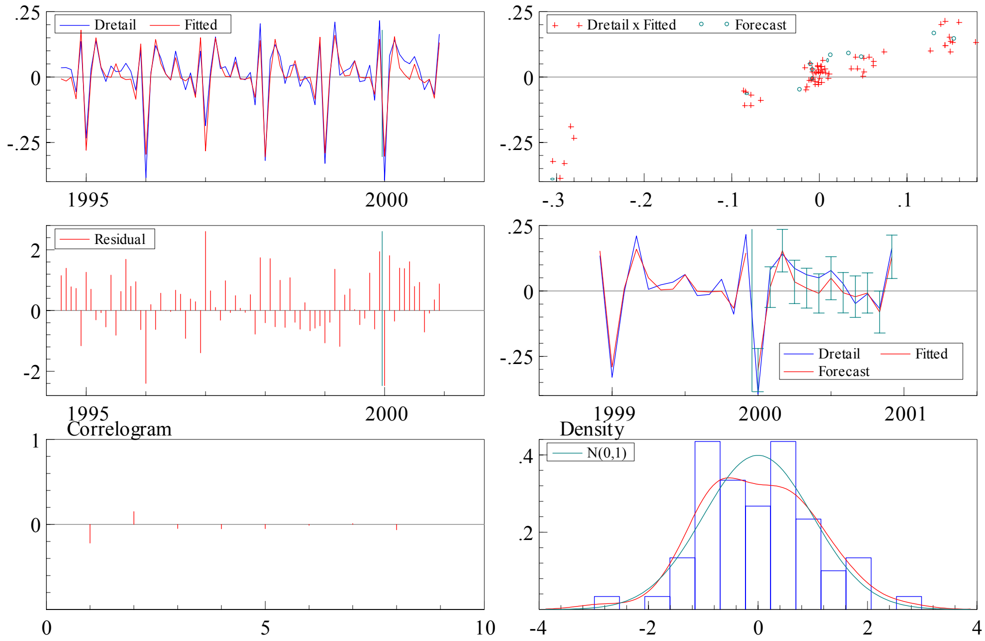

Fig. 6. Goodness-of-fit and graphical evaluation for the ECM model

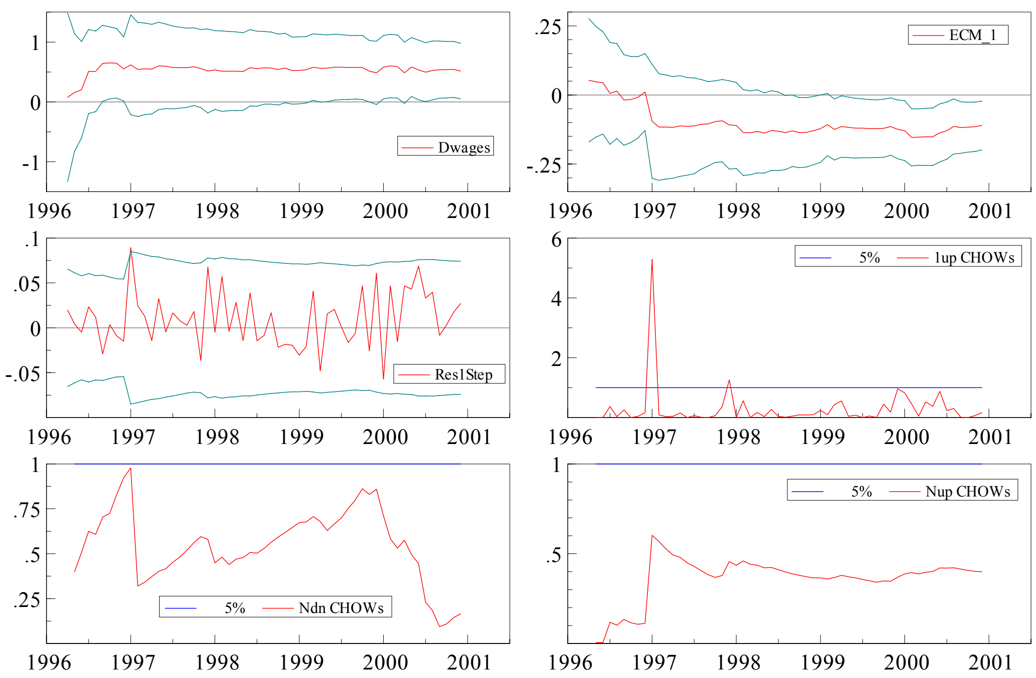

Fig. 7. Parameter constancy statistics for the ECM model

Legend for the figures

Fig. 1. Retail sales and average wages (logarithms), their first and 12th differences and empirical distributions (Gaussian kernel estimate).

Fig. 2. Autocorrelation (ACF) and partial autocorrelation (PACF) functions for retail sales and wages and for their first- and 12^{th}-differences

Fig. 3. Goodness-of-fit and graphical evaluation of model M_3

Fig. 4. Recursive estimates of coefficients in model M_3

Fig. 5. Recursive constancy statistics for model M_3

Fig. 6. Goodness-of-fit and graphical evaluation for the ECM model

Fig. 7. Parameter constancy statistics for the ECM model