Unit roots and the demand for cigarettes in Turkey: Pitfalls and possibilities.

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Abstract

The partial adjustment model for cigarette demand in Tansel (1993) is formulated as a restriction on the more general VAR model. The question whether the Tansel estimation results are spurious as claimed by Cameron and Collins (1998) is addressed in this framework. The role of intervention dummies and data transformations for the cointegration results is discussed in some detail. Finally, a more general model is estimated and two steady-state relations measuring demand and supply behaviour in the cigarette market are identified.

Keywords: Partial Adjustment Models, Cointegrated VAR, Intervention Dummies, Data Transformations, Identification.

JEL Classification: C3, E3.

1 Introduction[1]

Tansel (1993) (hereafter AT) discusses an empirical analysis of cigarette consumption in Turkey over the period 1960-1988 based on a partial adjustment model. Cameron and Collins (1998) (hereafter CC) argue in a reply to her paper that the partial adjustment approach is flawed because the data contains unit roots and that the results in AT are an artefact of dummies or time trending.

The discussion highlights some of the challenges of empirical work in economics as a result of the "unit root revolution" and the consequent need to properly account for integration and cointegration properties of the data. Since many applied economists are likely to be favorable

[1] I am grateful to Aysyt Tansel for many clarifying remarks on the data and the Turkish institutions.

to the partial adjustment approach by AT, still widely used in applied economics[2] I will here take the opportunity to re-analyze the Turkish cigarette data with the purpose of sorting out the diverging views and results of the two papers. In doing so I will address the following questions: Were the results in AT spurious? Is it possible to reproduce them in a more general framework? How big are the costs of ignoring unit roots and cointegration? At the same time I will discuss some frequent pitfalls in empirical analysis when data contain unit roots and demonstrate the additional possibilities given by unit-root data. It is my hope to convince the applied economists that unit roots are not necessarily a nuisance but, instead, when properly understood can provide some powerful tools for confronting theory with reality.

2 The empirical problem[3]

AT estimates four different models, three of which are based on partial adjustment towards desired (steady-state) consumption, and one is a static regression analysis. All four models include the following three basic variables (see AT for a detailed description of the variables) in logs:

1. per adult cigarette consumption, $C_t^a = C_t - N_t^a$, where C_t is aggregate cigarette consumption inclusive black market cigarettes in year t and N_t^a is the Turkish population over 15 years of age,
2. the real price of cigarettes, $Pc_t^r = Pc_t - P_t$, where Pc_t is the price of cigarettes and P_t is the consumer price index, and
3. real per capita gross national product, Y_t^c.

Furthermore, two step dummy variables, $D1_t$ and $D2_t$, defined as $D1_t = 1$ for t = 1982,...,1988, and $D2_t = 1$ for t = 1986,...,1988, 0 otherwise, measure a potential decline on cigarette consumption associated with a health warning on cigarette packages since the end of 1981, and with anti-smoking campaigns in 1986-88. Finally, the effect of education on cigarette consumption was estimated by additionally including two variables measuring (the logs of) secondary, ${E^s}_t$, and tertiary, E_t^t, enrollment ratios. All models were estimated as single equation models.

Before embarking on the econometric analysis it is useful to have a look at the data. Figure 1 show graphs of the levels and differences of

[2] For example, the Turkish demand for cigarettes has been used as an illustrative example of partial adjustment models by Ramanathan (1998)

[3] All empirical results have been calculated using the software program CATS in RATS (Hansen and Juselius, 1994) and GiveWin (Doornik and Hendry, 1998).

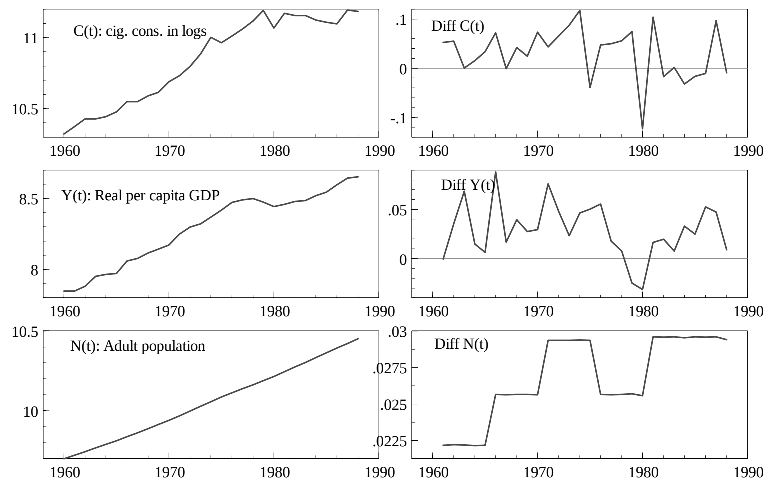

Figure 1: The logs of cigarette consumption, real per capita GNP, and the adult population graphed over the period 1960-1988.

aggregate cigarette consumption, C_t,(upper panels), of per capita GNP, Y_t^c, (middle panels), and of the adult population, N_t^a, (lower panels). Similarly Figure 2 show cigarette prices, Pc_t, (upper panels), CPI prices, P_t, (middle panels), and real cigarette prices, $Pc_t - P_t$, (lower panels) and Figure 3 secondary enrollment ratios, E_t^s, (upper panels) and tertiary ratios, E_t^t, (lower panels). All variables are in logs.

A visual inspection of the graphs demonstrates that the variables in levels are strongly trending, supporting the worries by CC about unit roots in the data. Furthermore, the nominal price series in levels and differences in Figure 2 show some evidence of explosive behaviour, typical of fast growing inflation periods. However, the real price should not exhibit explosive behaviour if cigarette prices and consumer prices follow the same explosive behaviour, i.e. share the same explosive trend in a one to one relationship. This seems more or less to be the case, although the differenced real cigarette price series still show some evidence of instability at the end of the sample. The differenced population variable graphed in Figure 1 exhibits stepwise changes as a consequence of counting the population once every 5 years. Furthermore, the differenced tertiary enrollment variable, E^t, in Figure 3 exhibit some wild swings between 1975 and 1985.

These features of the data will have to be properly accounted for to secure correct statistical inference. This will be discussed in the subsequent econometric analysis.

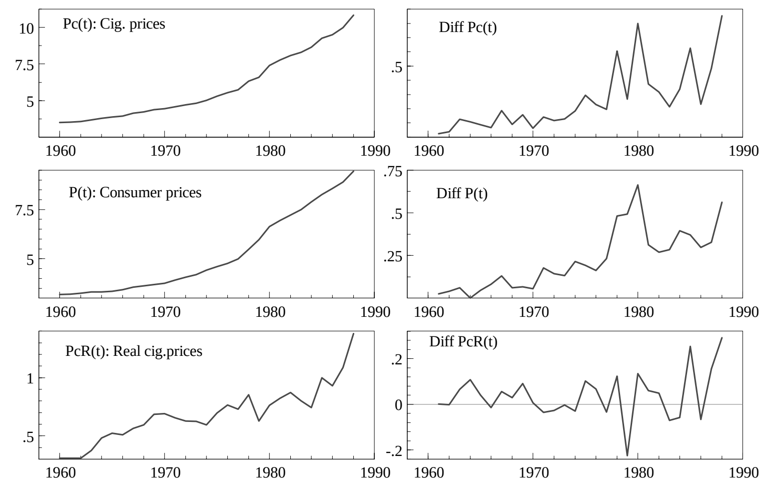

Figure 2: The logs of cigarette prices, CPI prices, and real cigarette prices in levels and differences graphed over 1960-1988.

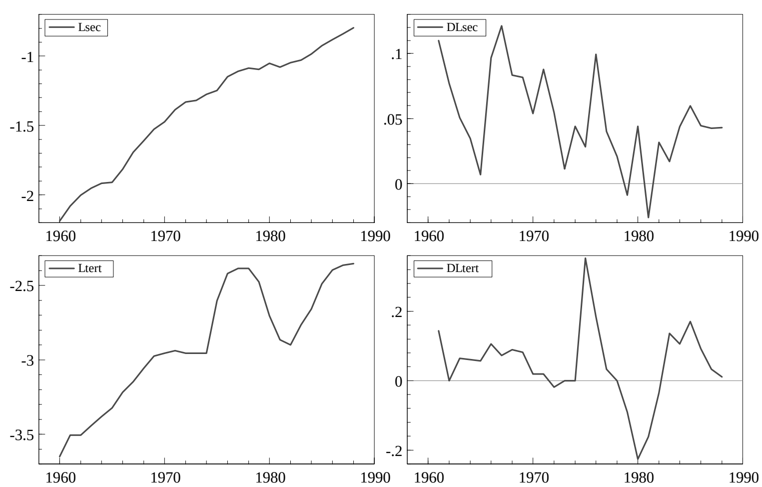

Figure 3: The logs of secondary and tertiary enrollment ratios over the period 1960-88.

3 The VAR formulation

CC claim that the long-run steady-state relation found in AT is an artefact of the included dummy variables or the result of spurious regression of trending variables. They support their claim by first showing that the data contain unit roots using augmented Dickey-Fuller tests, and then testing for cointegration in a VAR model of the three basic variables with and without the two dummy variables and finally without dummies but instead with a trend in the cointegration space.

Before defining the empirical models I will first discuss the properties of the variables from the point of view of statistical versus economic modelling. In general, the distinction between stochastic variables, $z_t' = [C_t, Pc_t, P_t, Y_t^c, N_t^a, E^s{}_t, E_t^t]$, and deterministic variables, $q_t' = [D1_t, D2_t]$, determines the scope of the statistical model, whereas the distinction between endogenous, y_t, and exogenous, x_t, variables determines the scope of the economic model. The analysis in AT is based on the implicit assumption of one endogenous variable, C_t^r, based on the argument that prices are set by the state monopoly Tekel. Nevertheless, one cannot exclude the possibility from the outset that prices have been influenced by cigarette consumption. Therefore, the classification of the stochastic variables into $z_t' = [y_t, x_t]$, where $y_t = [C_t, Pc_t]$ and $x_t = [P_t, Y_t^c, N_t^a, E^s{}_t, E_t^t]$ seems motivated.

In cointegrated VAR models the closest counterpart to the classification into endogenous and exogenous variables is into variables exhibiting long-run feed-back and variables which do not. The latter are often called (long-run) weakly exogenous variables. An important difference is that exogeneity in an economic model is an assumed property of a variable, whereas weak exogeneity in an econometric model is a testable property of the empirical model. Therefore, weak exogeneity should if possible be tested empirically within a fully specified VAR model. Assume for simplicity a VAR(2) model:

$$\Delta z_t = \Gamma \Delta z_{t-1} + \Pi z_{t-1} + \mu + \varepsilon_t, \tag{1}$$

where ε_t is $NI_p(0, \Omega)$. The reduced rank, r, of $\Pi = \alpha\beta'$, where α and β are $p \times r$, is tested with the likelihood ratio test procedure, the so called trace test. For a given value of r, long-run weak exogeneity can be tested as a zero row restriction on the adjustment coefficients α. Note that the trace test and the simulated asymptotic distributions are only valid for a fully specified VAR system (Harbo & al., 1998).

The present data consist of a total of only 29 yearly observations, which imposes an important restriction on the number of estimated parameters[4]. I will, therefore, estimate and test for cointegration in a simple VAR(1) for per capita consumption, real price, and per capita real GDP based on two versions of the basic model in AT. The first version, Model A, has no dummies, whereas the second version, Model B, allows the dummy variables to affect the equilibrium mean. Subsequently, in Section 7 I will relax the per capita and real price restriction used by AT and re-estimate the VAR model in more general form so that the adequacy of the assumed restrictions can be tested. The effect of education and anti-smoking campaigns will then be investigated by gradually extending the model.

Models A and B are defined by:

$$\text{Model A: } \Delta w_t = \Pi w_{t-1} + \mu + \varepsilon_t, \tag{2}$$

where the transformed variables $w_t' = [C_t^c, Pc_t^r, Y_t^c]$ and

$$\text{Model B: } \Delta w_t = A\Delta q_t + \widetilde{\Pi}\widetilde{w}_{t-1} + \mu + \varepsilon_t, \tag{3}$$

where $\widetilde{w}_t' = [w_t, q_t]$, $\widetilde{\Pi}$ is 3×5 and $t = 1961,...,1988$. Model B is the VAR model counterpart of the partial adjustment model 1 in AT. Model A is needed to discuss the spurious cointegration claimed by CC. Based on these two models I will discuss:

1. unit roots and cointegration testing,
2. stability measured by the roots of the system,
3. the role of dummy variables in the empirical model, and
4. systems versus single equations.

4 Unit roots or not?

CC raise the question of unit roots in the data and the consequences for estimation and inference. Information about the number of unit roots can be found both from the roots of the model, i.e. the roots of the characteristic polynomial, and from the reduced rank of the Π matrix. If the variables are at most I(1), the number of unit roots in the model and in the Π matrix should be the same. The intuition behind this is evident from the VAR formulation (1): if $x_t \sim I(1)$, then $\Delta x_t \sim I(0)$ and the only place unit roots can appear in (1) is in the levels matrix Π. If on the other hand $x_t \sim I(2)$, then $\Delta x_t \sim I(1)$ and both Γ and Π

[4]Estimating the full VAR model with 2 lags and 2 dummy variables would only leave a few degrees of freedom for estimation.

will contain information about the number of unit roots in the model. Figure 2 shows that inflation rates may not be stationary, so the latter possibility might be relevant for the subsequent models C and D, where the real price restriction is relaxed.

The reduced rank of $\Pi = \alpha\beta'$ is usually tested by solving an eigenvalue problem which delivers p eigenvalues λ_i and the corresponding eigenvectors β_i. If $x_t \sim I(1)$ there are $p - r$ eigenvalues equal to zero, corresponding to $p - r$ unit roots, i.e. $p - r$ common stochastic trends in the model. The r first eigenvectors correspond to the stationary cointegration relations $\beta_i' x_t$ which are often interpreted as economic steady-state relations. The λ_i are squared canonical correlation coefficients measuring the correlation between the $\beta_i' z_t$ and a linear combination of the (stationary) differenced process Δx_t. Hence, the larger λ_i the more likely is $\beta_i' z_t$ to be stationary. The so called trace test is a likelihood ratio test procedure for the null hypothesis that $\lambda_i = 0$, $i = r + 1, ..., p$.

There are three possibilities:

- $r = 0$, $p - r = 3$ unit roots in the model. Hence, there are no long-run steady-state relations in the data, i.e. the case claimed by CC,

- $r = 1$, $p - r = 2$ unit roots in the model. Hence, there is just one long-run relation, i.e. the case assumed implicitly by AT,

- $r = 2$, $p - r = 1$ unit root in the model. Hence, there are two long-run relations, and the steady-state relation estimated by AT could be a linear combination of these two. This is the case discussed in Section 7.

- $r = 3$, no unit roots in the model. Hence, all variables are stationary.

The eigenvalues, the trace test statistics, and the roots of the characteristic polynomial of the model are given in Table 1[5]:

When testing a hypothesis one can make an error of type I (rejecting the true null hypothesis) or type II (accepting the wrong null hypothesis). Generally, we would like a test procedure to produce both a small type I error (5%) and a small type II error (high power). The trace test is based on the null of $p - r$ unit roots which is a natural statistical hypothesis since a root on the unit circle is a simple hypothesis whereas stationarity (a root < 1.0) is a composite hypothesis. From an economic point of

[5] All estimated models have been checked for misspecification (normality, autocorrelation, and ARCH). They seem well specified.

Table 1: Misspecification tests, characteristic roots, and the trace test

	Model A (no dum.)			Model B (dummies)		
R^2	0.11	0.36	0.14	0.51	0.53	0.03
λ_i	0.41	0.20	0.00	0.74	0.37	0.09
The trace test	21.1	6.1	0.0	**53.6**	**15.7**	2.8
(90% *crit.values*)	(26.7)	(13.3)	(2.7)	(26.7)	(13.3)	(2.7)
The roots of the process	0.99	0.79	0.27	0.96	0.37	0.37
$r=2$	1.00	0.80	0.26	1.00	0.37	0.37
β_1'	1.00	0.66	-0.82	1.00	0.33	-0.68
β_2'	-0.30	1.00	-1.00	-0.81	1.00	-0.25
α_1'	-0.07	$\mathbf{-1.00}$	-0.06	$\mathbf{-0.45}$	$\mathbf{-1.16}$	-0.086
	(-0.5)	(-3.8)	(-0.7)	(-3.0)	(-4.1)	(-0.8)
α_2'	0.13	-0.14	0.07	**0.25**	$\mathbf{-0.44}$	0.04
	(1.8)	(-1.2)	(2.0)	(3.8)	(-3.5)	(1.1)

view the null of a unit root is not always a natural hypothesis. For example, in the case of cigarette consumption the null of one or two unit roots seems plausible, but not necessarily three unit roots[6]. When the sample size is small, the null of a unit root is very hard to reject. This can lead to the unfortunate situation that we may have to accept the null of no cointegration even when we strongly believe in cointegration and the estimates are economically plausible.

Model A with three variables leaves 24 effective observations for estimation, Model B with the two dummies reduces the number furthermore. The trace test of no cointegration is based on a test statistic $T\Sigma_{i=1}^{p}\ln(1-\lambda_i)$, so even when λ_1 is quite large (far from zero as in the present example) multiplying with a small T may, nevertheless, not produce a test statistics large enough to reject the null. Of course this only tells us the data contains little information about unit roots when the sample is small. But the consequence of following formal test procedures is that cointegration will often be rejected in small samples even when it is there, i.e. the test has low power. Simulation experiments have shown that when the size of the test (the type I error) is correct, say 5%, the power is about the same magnitude, i.e. the type II error is very high (Jørgensen, 2000). In large samples the opposite is likely to be the case: roots even very close to the unit circle, like $(1-\lambda_i)=0.99$ will be found statistically different from one if T is large enough. Hence, the interpretation of cointegration as evidence of long-run relationships in the data has to be done with caution (Juselius, 1999, 2001).

To avoid making type II errors (in particular when the null of cointegration is more natural than the null of a unit root) one can use other

[6]This would imply no equilibrating force between prices, consumption and income.

information in the model, for example, the magnitude of the largest root left in the model after choosing the cointegration rank r, the significance of the α coefficients to the $r'th$ cointegration relations, the stability and interpretability of the cointegration relations, etc. (for further discussions, see Hendry and Juselius, 2001).

The Turkish cigarette consumption provides a good example of this. In Model A the hypothesis of three unit roots cannot be rejected on the 10 % level, although the largest eigenvalue, $\lambda_1 = 0.4$, corresponds to a correlation coefficient of approximately 0.65 between the first cointegration relation and the differenced (stationary) process. The roots of the characteristic polynomial in Table 1 are consistent with at least one unit root, possibly two, but the smallest root, 0.3, seems to suggest at least one stationary direction.

In Model B the inclusion of the anti-smoking dummies improve the stability of the cointegration relations: the first relation, $\widetilde{\beta}_1' x_t$,[7] has a $\lambda_1 = 0.75$, i.e. corresponds to a correlation coefficient of approximately 0.85. Although adding the two dummies has increased the trace test statistics, it also has invalidated the asymptotic distributions (as of course has the small sample size!). The roots of the characteristic polynomial suggest as before one root very close to the unit circle, whereas the next one is only 0.4, i.e. significantly smaller than in Model A.

Obviously, adding the dummies has significantly improved stationarity. This is also evident by examining the adjustment coefficients α_1. In Model A cigarette consumption is not significantly adjusting towards $\beta_1' w_t$, whereas in Model B there is strong adjustment towards $\widetilde{\beta}_1' \widetilde{w}_t$. The coefficients of β_1 and $\widetilde{\beta}_1$ are quite similar, potentially describing steady-state cigarette consumption as negatively related to real cigarette price and positively to real income. The coefficients are similar to the long-run solution of Model 2 in AT. Table 1 also reports the second cointegration relation for both models. It corresponds to an eigenvalue $\lambda_2 = 0.2$ in Model A and to $\lambda_2 = 0.4$ in Model B. None of the α_2 coefficients of Model A are significant on the 5 % level[8], consistent with the small value of λ_2. Hence, including the second cointegration relation in model A would be useless. On the other hand, in Model B two of the α_2 coefficients are possibly significant, again demonstrating the importance of the dummy variables for the cointegration results.

[7] The coefficients to the dummy variables are not reported in Table 1.

[8] When we are dealing with nonstationary data, a Dickey-Fuller type of t-distribution is likely to be more appropriate than Student's t-distribution.

5 Dummies or not?

As pointed out by CC, the question whether it is sensible or not to include the two dummies in the model seems crucial for the interpretation of the partial adjustment models in AT as a description of a long-run demand relation for cigarettes. Many economists doubt the validity of using dummies, claiming that the latter tend to make theory look empirically correct when in fact the good fit is an artefact of the dummies. Let us consider two hypothetical scenarios:

- The Turkish authorities launch an anti-smoking campaign which is successful in the *ceteris paribus* sense: It makes people smoke less than before, given the real price of cigarettes and the real income level.

- The Turkish authorities launch an anti-smoking campaign which has no effect. However, for some other reason people smoke less in the period of the campaign. Moreover the Turkish cigarette consumption has nothing to do with real cigarette price nor with real income level.

Under the first scenario, failing to properly account for the drop in consumption associated with the anti-smoking campaign (assuming that the drop is not related to changes in real cigarette price or real income) is likely to bias the estimates of price and income elasticities and cointegration will be rejected[9]. Hence, including the dummies is a way of empirically accounting for the *ceteris paribus* assumption prevalent in theory models. As demonstrated in Juselius and MacDonald (2000) it often makes theory come out more clean.

Under the second scenario, including the dummies will spuriously explain some variation in the data unrelated to the anti-smoking campaign. Furthermore, this will help to produce some steady-state estimates of price and income elasticities which are plausible but, nevertheless, only artifacts of the dummies.

In economics where controlled experiments are difficult, or impossible, it is hard to conclusively distinguish between the two scenarios: an economist having confidence in theory and the effectiveness of anti-smoking campaigns would probably stick to the first scenario as his/her maintained prior, whereas more sceptical persons, like CC, would probably insist on the second scenario as a reasonable prior.

[9] This is because cointegration residuals will now contain some cumulative effects of permanent shocks to cigarette consumption not being accounted for by the variables of the model.

Since I feel more favorable to the former group believing in the empirical usefulness of economic structures after appropriately accounting for the *ceteris paribus* assumptions by including other relevant information than theory information in the empirical model, I will her continue the empirical analysis of cigarette consumption allowing for dummies in the model.

6 Single equation or system?

From an econometric point of view the estimates of a long-run steady-state relation based on a single equation model for y_{1t} are equivalent to the estimates based on a fully specified cointegrated VAR model when the following two conditions are satisfied:

1. the cointegration rank is one,
2. the adjustment coefficients $\alpha_{1i} = 0$, $i = 2, ..., p$.

The first condition states that there exists only one stationary relation between the nonstationary variables included in the cointegration space. Hence, $r = 1$ implies $p-1$ stochastic driving trends in the model. When p is moderately large ($>$ 3 variables) the latter condition is often implausible from an economic point of view, at least if one believes in equilibrating economic forces (Juselius, 1999). Under the first condition there is only one steady-state relation, which is supposed to be a long-run cigarette demand relation. The estimates of the second cointegration relation of Model B tentatively suggests a price relation (positively related to cigarette consumption) with a quite strong adjustment coefficient in the real price equation ($\alpha_{22} = -0.44$, t-ratio -3.5). Hence, the empirical evidence suggests that the assumption of just one cointegration relation might be questionable.

Assuming that $r = 1$, the second condition implies no feed-back effects on any of the other variables of the system when cigarette demand deviates from its long-run steady-state path. Only the adjustment coefficient in the cigarette consumption equation should be significantly different from zero. The adjustment coefficient to cigarette prices in Table 1 is, however, significant ($\alpha_{12} = -1.17$, t-ratio -4.1), whereas the adjustment coefficient to real GDP is clearly insignificant as *a priori* expected. Hence, the second condition may not be satisfied.

I will now compare the long-run solution of a partial adjustment model similar to Model 1 in AT with a static regression model, similar to Model 3 in AT, and with the cointegration results of Model B for $r = 1$. The derived long-run solutions are given in Table 2:

Table 2: Comparing long-run steady-state solutions

	C_t^a	$P^r c_t$	Y_t^c	$D1_t$	$D2_t$	α_{11}
Partial adj. model	-1.0	-0.25 (2.0)	0.65 (6.5)	-0.13 (3.0)	-0.07 (1.4)	-0.69
Static regr. model	-1.0	-0.22 (-2.4)	0.63 (9.1)	-0.10 (3.8)	-0.10 (2.7)	-
Cointegr. VAR B	-1.0	-0.33 (-4.2)	0.68 (12.4)	-0.11 (-5.9)	-0.03 (1.1)	-0.45

Note: t-ratios in brackets

The estimated price and income elasticities are very similar for all models. The calculated t-ratios differ to some extent, which illustrates the fact that unit roots in the data are more important for the distribution of coefficient estimates than for the estimates themselves. For example, the static regression model gives unbiased estimates but the OLS formula for standard errors of estimates tend to strongly underestimate the true values. The more autocorrelated the residuals, the worse. See discussion in Hendry and Juselius (2000). Therefore, a partial adjustment model that allows for at least some dynamics in the model usually performs much better than the static regression model. Nevertheless, the estimated standard errors are biased in both models.

The estimated standard errors of the long-run parameters β from the cointegrated VAR model are asymptotically correct, but can deviate substantially from their true values in small samples (Johansen, 2000, 2001). The reason why all three methods appear to do quite well in this example is because most of the dynamic adjustment in cigarette consumption has been completed within a year. In Model B, the adjustment coefficient $\alpha_{11} = -0.45$ indicates that approximately half of the adjustment has taken place within a year, which is consistent with a DW statistic of approximately 1.4 in the static regression model. In the partial adjustment model the coefficient to lagged consumption was 0.31.

So unmodelled unit roots in the data can, but need not, have serious effects on estimation and inference. As long as the residuals are reasonably clean (not autocorrelated) estimation results need not be unreliable. However, as discussed above, this conclusion is valid under the assumption of one cointegration relation and no significant feed-back effects on the other variables in the system. When this is not the case a fully specified system will outperform the single equation model, often very significantly so.

As discussed above, the conditions for efficient estimation using a single equation model may not be satisfied in the present example. Therefore, I will take the discussion one step further in the next section and analyze the Turkish cigarette consumption data as a system assuming two cointegration relations one for cigarette consumption and the other for cigarette price.

7 The per capita and the real transformation

Model B was based on real price and per capita transformations both of which imply testable cointegration restrictions. Therefore, I will here relax the restrictions and do a proper cointegration testing based on the original data. Moreover, I will discuss estimation in partial systems which can be motivated when the number of original variables is quite large and the sample size is small. Finally, the trace tests, the characteristic roots, and the significance of the adjustment coefficients suggested that there may very well be two stationary cointegration relations. In the case of two cointegration relations identification becomes an important issue.

The rapid growth in nominal prices over this period makes even small deviations from long-run price homogeneity potentially important from an econometric point of view. This is particularly so because the long-run nominal price trend was shown to contains a small explosive root (1.03). Econometrically this has to be accounted for either by transformation as done in AT, or by conditioning as will be illustrated below. Similarly, the per capita formulation of the cigarette consumption is based on some untested hypotheses about the temporal distribution of the Turkish population as well as the distribution of smokers.

To check these implicit assumptions I will first start the empirical model analysis by relaxing the real price restriction and the per capita restriction for Model B in Table 1 under some assumptions of weak exogeneity to be further discussed below. In this model, Model C, I will test the real price and the per adult capita restriction as well as long-run exclusion restrictions. Model C is defined by:

$$\text{Model C: } \Delta y_t = A_1 \Delta x_t + A_2 \Delta q_t + \alpha\beta' \widetilde{y}_{t-1} + \mu + \varepsilon_t, \qquad (4)$$

where $y_t' = [C_t, Pc_t]$, $x_t' = [P_{t,} Y_t^c, N_t^a]$, $q_t' = [D1_t, D2_t]$ and $\widetilde{y}_t' = [y_t, x_t, q_t]$. The estimates of α and β are given in Table 3. Model C is a partial model based on a (untested) weak exogeneity assumption of consumer prices, real income, and adult population. It implies that the latter variables have influenced cigarette prices and consumption, but have not been influenced by them. The estimates of α in Table 1 showed that weak exogeneity of Y_t^c was supported by the estimates of Model B, whereas the impact of cigarette consumption and prices on consumer price index and population *a priori* could be assumed small.

Table 3: A more general specification

	C_t	Pc_t	P_t	Y_t^c	N_t^a	$D1_t$	$D2_t$
β_1'	1.00	0.32	-0.35	-0.80	-0.69	0.16	-0.01
β_2'	-0.06	1.00	-0.73	1.60	-4.07	-0.22	-0.27
α_1'	$\underset{(-3.0)}{-0.38}$	$\underset{(-4.3)}{-1.11}$					
α_2'	$\underset{(3.5)}{0.30}$	$\underset{(-3.3)}{-0.55}$					

Hypotheses tests:	$\chi^2(\nu)$	ν	p-value
Test of real price restriction	1.61	2	0.45
Test of per capita restriction	1.15	2	0.56
Test of long-run exclusion of N_t^a	1.40	2	0.50
Test of long-run exclusion of $D1_t$	12.51	2	0.00
Test of long-run exclusion of $D2_t$	1.83	2	0.40

The assumption that the conditional process $\{y_t \mid x_t, q_t\}$ does not contain explosive roots is supported by the estimated roots of the characteristic polynomial: [0.42, -0.17]. Nevertheless, x_t is a nonstationary process and conditioning on it has consequences for the statistical analysis. For example, the trace test is no longer valid in partial models like (4) (see Harbo et al., 1998). The largest root of the conditional process, 0.42, suggests stationarity. The significance of the adjustment coefficients α_1 and α_2 in Table 3 are consistent with this interpretation. Hence, I proceed with the assumption that $r = 2$.

The estimates in Table 3 show that the price effects are similar to Model B, whereas the income effects have now become larger and much closer to unit coefficients. The test of the real price restriction $R\beta = 0$, where $R = [0, 1, 1, 0, 0, 0]$ was clearly accepted with a p-value of 0.45. This indicates that the real transformation, $Pc_t^r = Pc_t - P_t$, removes the explosive root in the data. A similar test result was obtained for the per adult capita restriction $R\beta = 0$, with $R = [1, 0, 0, 0, 1, 0, 0]$. This seemed more surprising, considering that the unrestricted coefficients do not seem to satisfy this restriction. However, the hypothesis that N_t^a could be excluded from the long-run relations was strongly accepted. Hence, the informational content of the five-year population counts is so low for cigarette consumption that this variable can be discarded altogether. Moreover, the anti-smoking campaign dummy was also found to be quite insignificant in this model and was left out.

AT also investigates the effect of education on cigarette consumption, by including information about secondary, E_t^s, and tertiary, E_t^t, enrollment ratios. I tested this by including the two enrollment rate variables in a simplified version of Model C, in which N_t^a and $D1_t$ were left out.

Long-run exclusion of the tertiary enrollment variable could not be rejected (p-value 0.15) whereas the long-run exclusion of the secondary enrollment variable was rejected (p-value 0.04).

8 Identification

The final model, Model D, is specified as a VAR(1) model for cigarette consumption and cigarette prices with consumer prices, real income, secondary school enrollment rate, and the 1984-88 anti-smoking campaign as weakly exogenous variables, i.e.

$$\text{Model D: } \Delta y_t = A_1 \Delta x_t + A_2 \Delta q_t + \alpha\beta' \widetilde{y}_{t-1} + \mu + \varepsilon_t, \tag{5}$$

where $y_t' = [C_t, Pc_t]$, $x_t' = [P_t, Y_t^c, E_t^s]$, $q_t' = [D2_t]$ and $\widetilde{y}_t' = [y_t, x_t, q_t]$. As demonstrated above I have arrived at this model using a simplification search based on statistical criteria. The final important question to be answered is whether the estimated relations can be identified as economically meaningful steady-state relations for cigarette demand and supply.

When there are unit roots in the data we need to distinguish between identification of the long-run steady-state structure and the short-run dynamic adjustment structure. For both cases we need to demonstrate that the imposed structures are generically, empirically and economically identified (Johansen and Juselius, 1994).

The first criterium, generic identification, has to be satisfied in order to be able to uniquely estimate the coefficients, the second criterium, empirical identification has to do with statistical significance: is a generically identified parameter also statistically significant? The results of Table 4 demonstrate that both the long-run and the short-run structure are identified and that the imposed over-identified restrictions are strongly acceptable in both cases. All estimated coefficients are significant on the 5% level. Hence, the conditions for generic and empirical identification seem to be satisfied.

The third criterium, economic identification, is the most difficult. Do the two steady-state relations make economic sense as a demand relation and a pricing setting relation? A priori, it seems plausible that the measurements of cigarette consumption reflect demanded quantities (i.e. cigarette consumption has not been subject to supply restrictions), and that the measured prices are set by the state monopolist Tekel subject to various kinds of taxes. Given this can the estimated results be given a meaningful economic interpretation?

It was not possible to find significant current effects of cigarette prices and cigarette consumption, nor of current changes in per capita GNP in

Table 4: Identification of the long-run steady-state and the short-run adjustment structure

The long-run cointegration structure						
	C_t	Pc_t	P_t	Y_t^c	E_t^s	$D2_t$
$\widetilde{\beta}_1'$	1.00	0.0	0.0	-1.00	-0.14 (0.04)	0.08 (0.03)
$\widetilde{\beta}_2'$	0.00	1.00	-1.11 (0.025)	0.00	0.00	0.00

Notes: Standard errors in brackets, test of overidentifying restrictions: $\chi^2(\nu) = 1.79(5)$,p-value = 0.88.

The short-run adjustment structure				
		ΔP_t	$\widetilde{\beta}_1' x_{t-1}$	$\widetilde{\beta}_2' x_{t-1}$
ΔC_t	=	-	-0.51 (4.1)	$-$
ΔPc_t	=	1.14 (13.8)	-1.00 (-3.1)	-0.73 (-4.5)

Notes: t-values in brackets, Test of overidentifying restrictions: $\chi^2(\nu) = 1.45(2)$,p-value = 0.48.

the short-run adjustment structure of the model. Cigarette consumption in Turkey has an estimated long-run income elasticity of unity whereas the long-run price elasticity is essentially zero after accounting for the effects of the health warnings and the development of the secondary enrollment rate. The short-run adjustment towards the long-run steady-state consumption takes approximately two years. These results are not much different from Model 4 in AT. Cigarette prices seem to have increased somewhat more than proportionally to CPI prices both in the short-run and the long-run. Nevertheless, the estimated long-run CPI price elasticity, 1.11, is only borderline significantly different from unity. Cigarette prices adjust significantly both to both steady-state relations resulting in the combined steady-state relation:

$$-0.74(Pc - 1.11P)_t - 1.0(C - Y + 0.20E^s - 0.08D2)_t.$$

Although cigarette prices seem to have increased more than consumer prices in this period, the second relation suggests that they might have gone down with excess consumption relative to real per capita GNP. The effect of education is also negative, whereas the health scare campaign has a small but positive effect. The "excess consumption" effect seems surprising and would motivate further econometric sensitivity analyses[10].

[10]For example, when the black market cigarette consumption was not included in the analysis this effect disappeared. Hence, it might be a result of 'noisy' mea-

Therefore, whether the data and the model convincingly identify a cigarette demand and price setting relation can be discussed.

9 Conclusions

The reported VAR analyses suggested that the estimated long-run relations in AT based on the partial adjustment models survived most of the performed checks, in spite of the failure to properly account for unit roots in the data. CC in recognizing this failure demonstrated that the null of no cointegration could only be rejected with the help of the anti-smoking campaign dummies. However, a more detailed VAR analysis suggested that this was primarily the result of focusing too strongly on type I error without considering the very low power due to the small sample size.

In many ways AT did quite well: the dynamics in the data were approximately accounted for by the lagged cigarette consumption; the real price transformation was statistically acceptable, one cointegration relation seemed defendable, and the weak exogeneity assumptions implicit in the single equation model were almost acceptable. However, using the tools of "unit-root econometrics" and the insights that have been accumulated over the last decade(s) still seems to add an extra dimension to the empirical analysis. Last but not least importantly it acts as a safeguard against possible mistakes and, hence, should lead to more convincing scientific discussions.

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