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Tying up loose ends: A note on the impact of omitting MA residuals from panel energy demand models based on the Koyck lag transformation

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ABSTRACT

Energy demand functions based on Koyck lag transformation result in an MA error process that is generally ignored in estimated panel data models. This note explores the implications of this assumption by estimating panel energy demand functions with asymmetric price responses and an MA process modelled explicitly. It is found that although the models with an MA term might be preferred statistically, they result in inferential problems implying that there might be a need to revisit the specification of panel energy demand functions used in a number of previous studies.

JEL Classifications: C8, Q4.

Key Words: Koyck-lag transformation, Moving average errors,
Panel data, Aggregate energy demand

Tying up loose ends: A note on the impact of omitting MA residuals from panel energy demand models based on the Koyck lag transformation[*]

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1. Overview

Gately and Huntington (2002), Griffin and Schulman (2005), Huntington (2006) and Adeyemi and Hunt (2007) all imposed a first-order geometric (or Koyck) lag on prices when specifying their panel data demand functions for energy. This gives an econometric specification for demand where the reaction to prices is slower than that to income. As these papers note, deriving the estimating equation for these demand models implies a moving average (MA) error; however, none of them explicitly allowed for this in estimation. Adeyemi and Hunt (2007) noted that:

> *"Ideally [these models] should be estimated with an allowance for the MA(1) error process to avoid potential specification errors; but, as far is known, is not possible with current available econometric software." (p. 701).*

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This study addresses this concern by estimating a similar demand function for two alternative datasets explicitly allowing for the MA process, and assesses the implications.

2. Methodology

Based upon a first-order geometric (or Koyck) lag on prices the general equation for estimating an aggregate energy demand function is given by:[1]

$$e_{it} = \alpha + \lambda e_{it-1} + \beta\left(y_{it} - \lambda y_{it-1}\right) + \gamma_m p_{it}^{\max} + \gamma_r p_{it}^{rec} + \gamma_c p_{it}^{cut} + \sum_{i=1}^{N-1} \delta_i D_i + \sum_{t=1}^{T-1} \delta_t D_t + \mu_{it} - \lambda \mu_{it-1} \qquad (1)$$

Where all variables are in logarithms, e_{it} (country *i*, year *t*) is energy consumption, y_{it} is real income and D_i and D_t are country-specific and time-specific dummy variables respectively.[2] Real energy prices p_{it}, are decomposed as described by Gately and Huntington (2002) capturing the historical maximum $p_{it}^{\max}$, price rises below the previous maximum p_{it}^{rec} and price cuts p_{it}^{cut}. The residuals in (1) follow an MA process $\left(\mu_{it} - \lambda \mu_{it-1}\right)$, but the aforementioned studies discussed above replaced this with ε_{it} and estimated using non-linear least squares (NLS).

In order to estimate Equation (1) *with the MA term included*, a state-space representation estimated via a Kalman filter (KF) can be used as illustrated in the following (essentially tautological) derivation.[3] The energy demand function can be written in a state space form where:

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[1] See Griffin and Schulman (2005) and Adeyemi and Hunt (2007) for a formal derivation

[2] Griffin and Schulman (2005) suggested using time dummies in such models to capture energy-saving technical progress which Adeyemi and Hunt (2007) likened to the Underlying Energy Demand Trend (UEDT) concept introduced by Hunt et al. (2003a and 2003b).

[3] Panel data based applications of the Kalman filter can be found as far back as Bryson and Ho (1969), as described by Jones (1993). Nonetheless, as far as is known, the application of longitudinal state space models

$$e_{it} = \alpha + \lambda q_{it-1} + \beta\left(y_{it} - \lambda y_{it-1}\right) + \gamma_m p_{it}^{\max} + \gamma_r p_{it}^{rec} + \gamma_c p_{it}^{cut} + \sum_{i=1}^{N-1} \delta_i D_i + \sum_{t=1}^{T-1} \delta_t D_t + \mu_{it} + \xi_{it} \qquad (2)$$

is the ‘observation equation’ and ξ_{it} is defined by the ‘state equation’ and used to capture the moving average error process. Specifically, given the use of the Kalman filter, the state equation can be specified as a function of the previous period residual term:

$$\xi_{it+1} = \theta\mu_{it} \qquad (3)$$

Here θ represents the coefficient of MA adjustment. Given the Koyck lag derivation, all that remains to arrive at the desired specification for estimation is to restrict the MA term θ equal to $-\lambda$. This is achieved here by substituting $-\lambda$ for θ directly within the filter equations rather than restricting these terms to be the same. Such filters are widely used to model MA processes for time series data, and are therefore a natural choice for application here. For discussion and further illustration of how these filters can be used to model MA processes see for example Hamilton (1994).

The models including the MA terms, which are estimated using the data described in the following section, are compared with conventional NLS results that ignore the MA process. For consistency with the specifications tested in previous related literature, the general model is denoted Model III, and two additional restricted versions are also estimated in which i) the time dummies are removed (i.e. $\delta_t = 0$) designated as Model I; and ii) price symmetry is assumed (i.e. $\gamma_m = \gamma_r = \gamma_c$, represented simply as γ) designated as Model II (Huntington, 2006; Adeyemi and Hunt, 2007). In addition, to try and give an indication of whether in a

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for panel data has hitherto eluded the economics literature, but for a few examples, see for instance Chen (2009). There are examples of panel data studies with time varying parameters using other methodologies, for example Cai (2007) and Chang and Martinez-Chombo (2003) who use nonparametric methods, which are not recursive in nature and as such are less suited to modelling an MA process.

statistical sense different specifications are ‘preferred’ to alternative non-nested specifications, general J-tests are applied.

3. Data

Table 1: Summary statistics of Annual Datasets.

	1: Industrial Sector						2: Whole Economy					
Descriptive statistics:	e_{it}	y_{it}	p_{it}	$p_{it}^{\max}$	p_{it}^{rec}	p_{it}^{cut}	e_{it}	y_{it}	p_{it}	$p_{it}^{\max}$	p_{it}^{rec}	p_{it}^{cut}
Mean	4.272	1.801	1.947	0.115	0.204	-0.282	0.855	2.885	4.417	0.205	0.437	-0.605
Median	4.242	1.839	1.972	0.067	0.185	-0.286	0.922	2.938	4.458	0.120	0.441	-0.575
Minimum	2.875	1.258	1.542	0	0	-0.747	-1.488	1.256	3.592	0	0	-1.386
Maximum	5.642	2.024	2.201	0.480	0.722	0	1.844	3.704	5.006	0.940	1.292	0
General characteristics:												
Countries	15						17					
Start year	1962						1960					
End year	2003						2008					
Per capita	No						Yes					

Two alternative datasets are used. **Dataset 1** is that used by Adeyemi and Hunt (2007), thus facilitating direct comparison with their results given their stated concern regarding the MA errors. This annual data set is for the industrial sector of 15 OECD countries between 1962 and 2003, so that e_{it} is aggregate industrial energy consumption (ktoe) y_{it} is the index of industrial output (2000=100), and p_{it} is the industrial index of real energy prices (2000=100). **Dataset 2** is for the whole economies of 17 OECD countries 1960 to 2008, so that here e_{it} represents per capita total energy consumption (ktoe divided by population), y_{it} is per capita

GDP (billion 2000 US$ using PPPs divided by population) and p_{it} is the real index of aggregate energy prices (2005=100). The data are summarized in Table 1.[4]

4. Results

The results are given in Table 2. The non-nested J-tests for both datasets indicate that significant additional explanation is obtained by adding the residuals from the model with MA terms to the model without MA terms; but that adding the residuals from the model without MA terms to the model with MA terms is not significant. This suggests that explicitly modelling the MA terms makes a non-trivial statistical improvement to model performance for the datasets used, and hence suggests that statistically this is the preferred modelling approach.

However, the MA models are still not ideal. There are a number of observed instances of undefined standard errors in these specifications. According to Gill and King (2004) such problems are not uncommon in non-linear estimation problems implying the need to consider alternative model specifications in such circumstances. Furthermore, there is the additional problem that the lag adjustment coefficients (λ) in the MA models are generally uncomfortably close to 1.

Turning to the economic interpretation of the models, Table 2 shows that the coefficients are reasonably similar for the models with and without the MA terms. Furthermore, the time-dummies shown in Figure 1 generate broadly similar dynamics;[5] hence, from an economics

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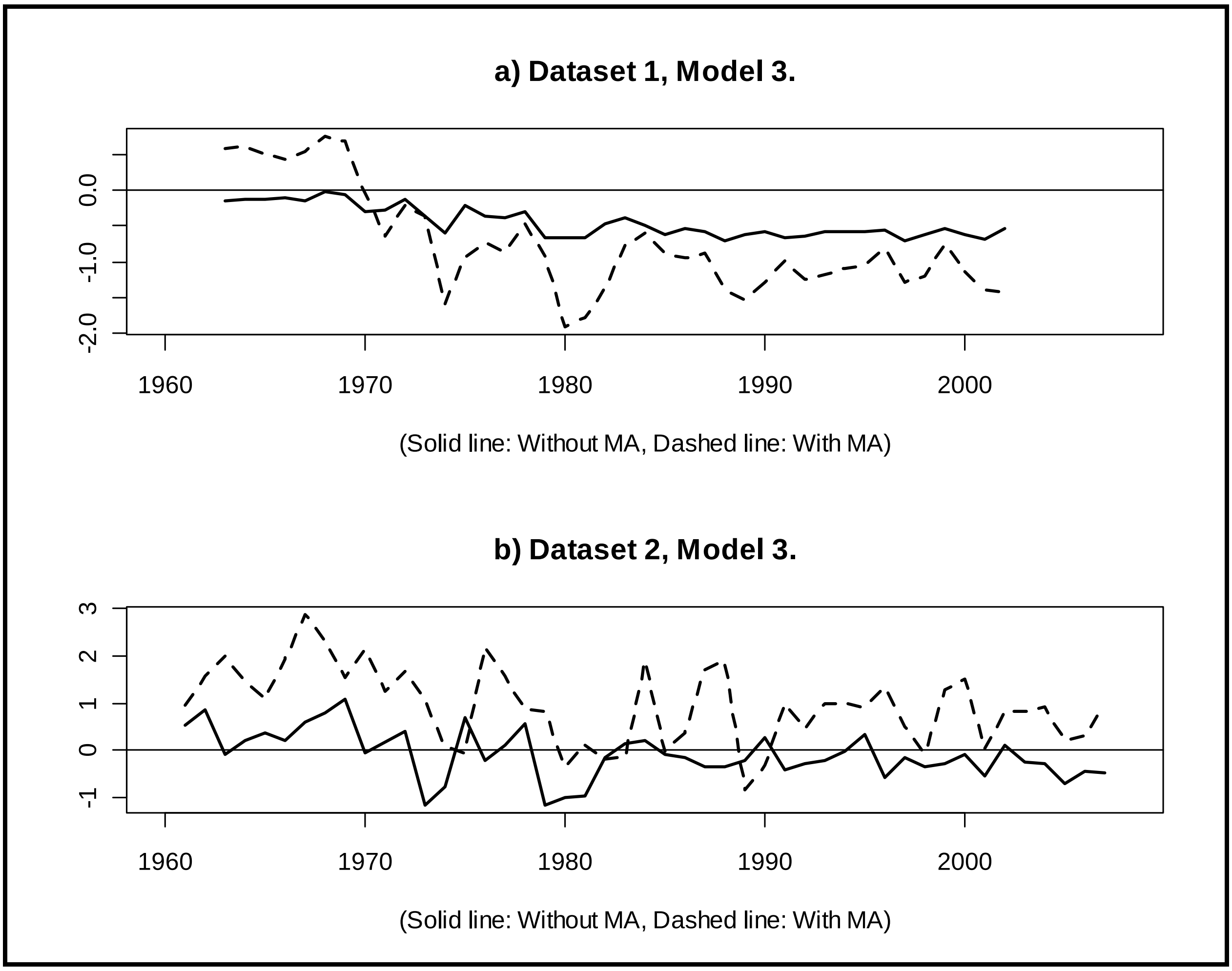
[4] Adeyemi and Hunt (2007) contains further details on the construction of **Dataset 1**, and further details on the construction of **Dataset 2** can be found in Adeyemi et al. (2010).

[5] See Griffin and Shulman (2005) footnote 18 for a description of how these are calculated.

perspective, little new is learnt by modelling the MA term. In particular, the inclusion or exclusion of the MA term would appear not to impact on the debate about whether to model asymmetric prices responses, given the relationships between the three models are very similar irrespective of whether the MA term is modelled explicitly or not.



a) Dataset 1, Model 3.

(Solid line: Without MA, Dashed line: With MA)

b) Dataset 2, Model 3.

(Solid line: Without MA, Dashed line: With MA)

Figure 1: Estimated long run time dummy coefficients.

5. Concluding remarks

This note addresses the importance of explicitly modelling the MA term in dynamic panel energy demand studies based on the Koyck lag transformation, given this has generally been ignored in previous studies. Some of the tests conducted suggest that statistically, the models with an MA term are preferred; however, these models also result in inferential problems due to poorly defined standard errors. Although, bootstrap type methods might be used to overcome this, the underlying issue of model mis-specification remains, hence the underlying Koyck lag structure (coupled with the implicit assumption of homogeneity across the countries) would seem too restrictive for the data used. This suggests that the energy demand models might need to be re-specified with a less restrictive lag structure and, as alluded to for instance by Adeyemi and Hunt (2007), should maybe take more direct account of country specific heterogeneity in the samples.

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Table 2: Estimation results (absolute t-values in parentheses).

	Dataset 1: Industrial Sector						Dataset 2: Whole Economy					
	-------------------Without MA-------------------			--------------------With MA---------------------			------------------Without MA------------------			--------------------With MA---------------------		
	Model I	Model II	Model III	Model I	Model II	Model III	Model I	Model II	Model III	Model I	Model II	Model III
Estimated parameters												
β	0.777	0.562	0.551	0.801	0.571	0.574	0.601	0.442	0.434	0.566	0.540	0.510
	15.565	8.916	8.811	27.156	12.066	13.569	10.563	7.433	7.261	17.281	17.446	NaN
γ		-0.014			0.050			-0.021			-0.010	
		-1.266			5.780			-2.282			-5.294	
γ_m	-0.036		0.019	-0.029		-0.006	-0.041		-0.009	-0.036		-0.009
	-3.214		1.163	-12.115		-1.170	-3.981		-0.704	-11.156		-2.553
γ_r	-0.047		-0.020	-0.061		-0.036	-0.076		-0.035	-0.050		-0.009
	-3.200		-1.071	-10.303		-5.366	-7.508		-2.609	-10.640		-2.614
γ_c	-0.021		-0.073	-0.037		-0.060	-0.051		-0.031	-0.022		-0.007
	-1.492		-3.002	-6.368		-4.603	-4.989		-1.994	-5.589		-2.448
λ	0.931	0.938	0.921	0.977	0.959	0.983	0.944	0.958	0.961	0.958	0.974	0.974
	83.871	81.983	64.765	NaN	1839.335	NaN	119.183	130.495	121.483	268.659	498.669	NaN
Diagnostics												
Time dummies	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Observations	615	615	615	615	615	615	816	816	816	816	816	816
Parameters	20	58	60	35	73	75	22	67	69	39	84	86
Log likelihood	1558.43	1614.56	1618.66	1783.32	1791.93	1854.10	1619.19	1745.69	1747.08	1906.81	2144.03	2182.11
Nested restrictions												
$\delta_t = 0$			120.472			141.563			258.465			458.692
$\gamma_m = \gamma_r = \gamma_c$			8.208			124.328			0.269			199.915
Non-nested restrictions												
$\psi=0$ (add Model II)	-0.052			0.088			290.044			-0.532		
$\varphi=0$ (add Model I)		0.898			0.293			161.377			0.375	
$\varpi=0$ (add KF)	-1.046	2.637	2.317				1.968	3.244	3.758			
$\omega=0$ (add NLS)				0.183	0.025	-1.081				-0.532	0.375	0.405

Notes:

(i) Nested restrictions tests report LR tests statistics. The degrees of freedom for the relevant chi-squared critical test-statistics are the difference in the number of estimated parameters between the restricted and unrestricted versions;

(ii) Non-nested restriction tests report the t-statistics for the fitted values included in the J-test auxiliary regressions;

(iii) ‘NaN’ indicates that the element of the Hessian matrix relating to the coefficient was negative; hence asymptotic inference is not feasible in the standard fashion.

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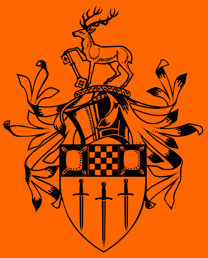

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