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How sensitive to time period sampling is the asymmetric price response specification in energy demand modelling?

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November 2012

SEEDS 138
ISSN 1749-8384

School of Economics
University of Surrey

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HOW SENSITIVE TO TIME PERIOD SAMPLING IS THE ASYMMETRIC PRICE RESPONSE SPECIFICATION IN ENERGY DEMAND MODELLING?

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ABSTRACT

The purpose of this paper is to investigate the criticism that energy demand estimates based on a specific price decomposition are sensitive to the chosen time period used for the estimation. To analyse this in a systematic way, different time series sample periods are constructed from annual data for 17 OECD countries covering the overall period 1960 to 2008. The specific price decomposition under consideration, often used to estimate asymmetric price response models of energy demand, separates the impact of prices above the previous maximum, of a price recovery below the previous maximum and of a price cut. Therefore, the analysis does not just involve using different time periods; instead, for each time period investigated, a new data set is constructed and for each data set, the price variable is decomposed in this way. An energy demand relationship allowing for asymmetric price responses is therefore estimated for each different sample period and the results suggest that recalculation of the decomposed price variables for each different period does affect the stability of the estimated energy demand responses. In contrast, a similarly estimated energy demand relationship with symmetric price responses for each different sample period is found to have less instability.

JEL Classifications: C23; C52; Q41.

Key Words: Energy demand modelling, Asymmetric price responses, Stability of estimates.

How sensitive to time period sampling is the asymmetric price response specification in energy demand modelling?[#]

Yaw Osei ADOFO[*], Joanne EVANS[**] and Lester Charles HUNT[***]

1. Introduction

In the face of the rising cost and growing demand for energy, concerns surrounding security of supply and challenging CO_2 targets, appropriate energy policy depends upon reliable and stable models of energy demand. History suggests that periods of high energy prices might have a lasting, dampening effect on demand. For example, the high energy prices of the 1970s resulted in increases in efficiency due to the installation of energy-saving technologies that remained in place despite a return to lower prices. This being the case, it has been argued that energy demand models with symmetric demand specifications do not provide an adequate description of energy demand. Consequently, estimates of elasticities and forecasts based on such models are likely to be misleading (Dargay, 1992).

Various model specifications have been put forward. An often quoted example is Gately and Huntington (2002),[1] which established that energy demand model specifications which ignore the asymmetric effects of prices on demand usually lead to an underestimation of the income elasticities and therefore to lower projections of energy demand and of carbon dioxide emissions. Griffin and Schulman (2005) criticized this particular asymmetric specification, arguing that using fixed-time effects to capture technical progress provided a better model

[#] **Acknowledgements**
This work builds upon and extends the work undertaken in Adofo (2009). We gratefully acknowledge the financial support provided by the Electricity Company of Ghana Ltd. We are also grateful to two anonymous referees for their comments and suggestions that have helped to improve the paper. Nevertheless, the views expressed in this paper are those of the authors alone and we are, of course, responsible for all errors and omissions.

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[1] The price decomposition method employed by Gately and Huntington (2002) has also been used in a number of other papers, for example Dargay (1992), Gately (1992) and Dargay and Gately (1997) amongst others.

specification than using separate price decomposition components. Furthermore, according to Griffin and Schulman (2005) the asymmetric price model used by Gately and Huntington (2002) and others "has the peculiarity of being dependent on the starting point of the data period so that parameter estimates are not robust across different sample periods" (p. 1).

The focus of this paper is on this criticism of the dependence of the asymmetric price responses specification on the starting point and hence the time period over which the dataset is drawn. To achieve this, different time series sample periods are drawn from an annual panel of 17 OECD countries covering the overall period 1960 to 2008 for per capita energy consumption, per capita real income and real energy prices. Given the price decomposition used by Gately and Huntington (2002) and others, which are required to estimate specific asymmetric price response models, this does not just involve using different time periods; instead, for each time period investigated, a new data set is constructed. Moreover, for each period, the price variable is decomposed into the asymmetric components that separately measure the impact of prices above the previous maximum (p_{max} for short), a price recovery below the previous maximum (p_{rec}), and a price cut (p_{cut}).[2] From this the effect of changing the start date for the construction of the decomposed price variable on the stability of the estimated price and income elasticities of energy demand are observed.

The paper proceeds with a brief review of the literature in Section 2; a discussion of the data in Section 3 and the methodology employed for analysis in Section 4. The empirical results of the estimation of the demand responses for each of the generated sample periods are presented in Section 5, along with an analysis of the estimated coefficient series obtained. Section 6 summarises and concludes.

2. Literature

Jones (1994) argues for a general model specification of energy demand that is "representative of the data generation process, capable of providing better estimates of the price and income elasticities needed for forecasting and policy analysis" (p. 252). One of the most important differences in energy consumption decisions compared to other demand

[2] The way these are calculated is discussed below.

sectors of an economy is that it is closely linked to the capital stock of energy-using equipment (Gately and Huntington, 2002). This is because each type of equipment embodies a technology that specifies a given level of energy use per unit of the services it produces thereby affecting the ability of energy users in responding in the long-run to price variations. Consumers' response therefore becomes a trade-off between their anticipated energy savings and full opportunity cost of replacing the old equipment with new ones (Ryan and Plourde, 2002a).

The inclusion of technical change in energy demand models is assumed by Beenstock and Willcocks (1981) and Hunt et al. (2003a and 2003b) to be primarily exogenous in nature, separate from the response to changing energy prices. Kouris (1983) argued that technical change is generally price induced; hence, in general it should be captured via the price response (or elasticity) in energy demand models. More recently, Adeyemi et al. (2010) have argued that general energy demand specifications should allow for both.

Furthermore, given some energy-saving technologies remain in place (such as loft insulation) despite falling prices, there is good reason to believe that high energy prices (such as those experienced in the 1970s and early 1980s) had a lasting, dampening effect on demand. Therefore, it has been argued by Dargay (1992), Dargay and Gately (1995), and others that symmetric energy demand functions (with or without an allowance for exogenous technical change) do not provide an adequate description of energy demand, likely making estimates of elasticities and forecasts based on such models misleading; hence, their argument for the inclusion of asymmetric price responses (APR). Energy demand models should therefore arguably allow for both price-induced technical progress in an asymmetric way and exogenous technical progress. However, Hunt et al. (2003a and 2003b) argued that the exogenous component should be suitably flexible to capture not only technical progress but also other non-systematic exogenous influences via what they call an underlying energy demand trend (UEDT). In summary, the most general energy demand specification is one that allows for the exogenous elements (via a flexible UEDT) *and* an APR (through a decomposed price variable); thus allowing for the distinction between the exogenous effects and the different induced effects of price shocks and rising and falling energy prices (Adeyemi et al., 2010).

However, this approach has not always been adopted with some debate in the literature on how it might be achieved. By ignoring the exogenous component, Gately and Huntington (2002) showed that energy demand responds differently to p_{max}, p_{rec}, and p_{cut} (although a similar asymmetry in income response was generally rejected). Griffin and Schulman (2005) suggested that the price decomposition approach used by Huntington and Gately (2002) is only a proxy for energy-saving technical progress and that a better alternative is to use fixed-time effects (time dummies).[3] However, Huntington (2006) rejects symmetry. By providing some coefficient restriction tests, not carried out by Griffin and Schulman (2005), Huntington (2006) demonstrates that both exogenous and price-induced technological developments represented in a model by fixed-time effects and APR (p_{max}, p_{rec}, and p_{cut}) respectively have a role (statistically) to play in understanding energy demand patterns. Adeyemi and Hunt (2007) corroborated this statistical finding for the OECD industrial sector.

Despite this, there is still argument in the literature about the use of APR *vis-à-vis* time dummies (or UEDT) in panel data estimation. According to Dargay and Gately (2010), the Griffin and Schulman (2005) approach produces coefficients that are constant across countries for a given year and can vary over time in an "unstructured manner" (p. 6276). This is in contrast to the view of Adeyemi and Hunt (2007) and Adeyemi et al. (2010). They argue that it is wrong to assume that the UEDT will be represented by a constant change over time given that technical progress and other exogenous factors are unlikely to change in such a way. Therefore, according to Adeyemi and Hunt (2007) and Adeyemi et al. (2010) when estimating panel energy demand models the time dummies suggested by Griffin and Schulman (2005) should be included and the estimated coefficients are very likely to be non-linear with periods when they are increasing or decreasing – i.e. they are likely to vary in an 'unstructured manner'.[4]

In addition, Dargay and Gately (2010) show that for G7 per capita oil demand there is a strong negative correlation between the fixed time effects and p_{max} arguing that demand reductions were likely to have been p_{max} induced; reflecting either endogenous technical

[3] Griffin and Schulman (2005) implicitly considered APR and fixed-time effects as substitutes, but suggested that fixed-time effects are better proxies for what the APR was initially proposed to tackle.

[4] It is worth adding that Adeyemi and Hunt (2007) and Adeyemi et al. (2010) do not rule out such a constant change if it is what the data suggests. They argue that any general energy demand specification should initially include a general non-linear UEDT. It is only if accepted by the data that a more restrictive version should be accepted.

change or fuel switching not reversed by price cuts. Dargay and Gately (2010) argue that the fixed time effects (the time dummies coefficients) "tell us nothing about the determinants of demand changes, in either the past or the future" (p. 6276). In summary, according to Dargay and Gately (2010) given the time dummies are not independent of prices (at least not p_{max}) they do not help explain demand and could be measuring anything. Unfortunately, Dargay and Gately (2010) do not report the tests undertaken by Huntington (2005) and Adeyemi et al. (2010) which would at least give a statistical basis to help determine whether there is a role for the time dummies and/or ARP.[5]

The above highlights the issues around the way technical progress (and other exogenous factors) might be incorporated in energy demand models be it exogenously via the UEDT or endogenously via the p_{max}, p_{rec}, and p_{cut} version of APR.[6] Consequently, in order to focus on the main criticism that estimated APR based on the p_{max}, p_{rec}, and p_{cut} decomposition depend upon the starting point and hence time period over which the dataset is drawn (discussed further below), models that include and exclude time dummies both with APR are estimated (as explained in Section 4 below).

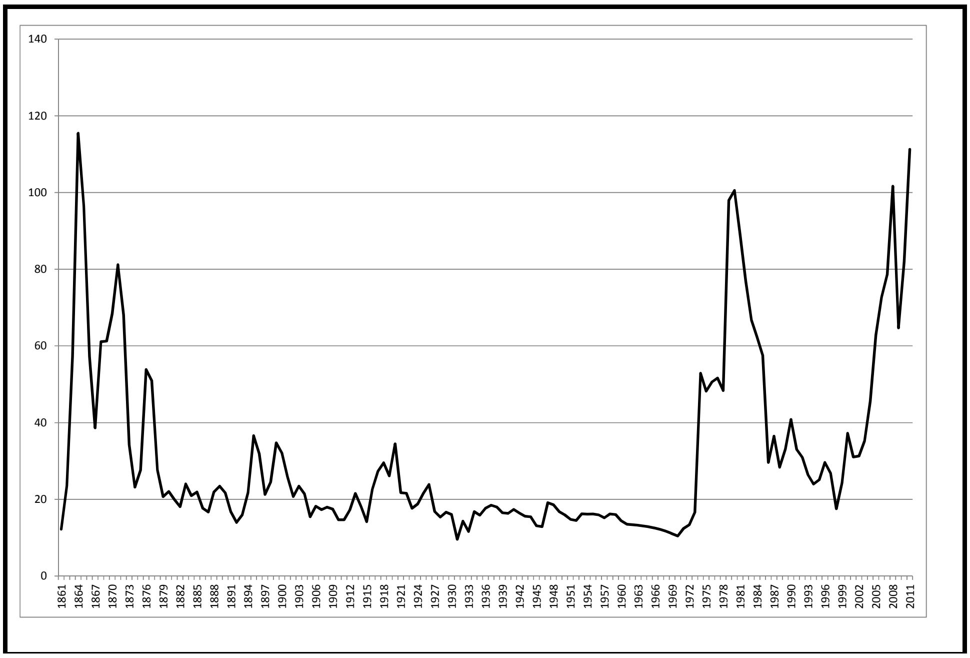
As highlighted one of the biggest criticisms of research that include APR based on the p_{max}, p_{rec}, and p_{cut} decomposition is their dependence on the starting point of the dataset and the implicit assumption that energy consumers have very long memories when there is a sustained period of falling prices (or prices rising and falling below the previous maximum). However, given that the decomposition approach is based on technical progress being price induced and the inclusion of p_{max} arguably reflects that when price was at its maximum, the induced efficiency change (such as the installation of loft insulation) continues to impact on

[5] These tests would give useful additional information on which to choose the preferred model, however, arguably this should not be used blindly without recourse to economic theory and intuition. As Adeyemi and Hunt (2007) notes, the "chosen model should be the one that is accepted by the data while at the same time conforming to economic theory—but this should be estimated and tested rather than imposed at the outset" (p. 707).

[6] It is worth noting that these are not the only criticisms of previous energy demand research that has incorporated APR. Adeyemi and Hunt (2007) suggest that in country panel data models a model specification that assumes that the slope and time coefficients are constant across the various countries is unrealistic in light of different socio-economic and institutional patterns and could lead to conflicting statistical and economic estimates. Moreover, they argue that the imposition of the same pattern of the UEDT, proxied by the fixed-time effects in the panel data context, is likely to be too restrictive. Adeyemi and Hunt (2007) also suggest that there might be problems with assuming a Koyck lag structure when modelling energy demand as used by Gately and Huntington amongst others. These are all issues that warrant further investigation, however, in order to focus on the specific p_{max}, p_{rec}, and p_{cut} decomposition issue, these are not considered here.

energy consumption decisions. Despite this, the decomposed series are conditional on the time period over which the data is drawn. A price increase can therefore be identified as p_{max} in one dataset but as p_{rec} in another dataset. This therefore raises questions on the robustness of the estimates obtained for different estimation sample periods, meaning that the relative importance of the three decomposed price variables appear highly sensitive to the time period sampled (Griffin and Schulman, 2005).

Figure 1: Crude oil prices 1861 – 2011 (US$2011 per barrel)



Source: BP (2012).

Indeed, as Figure 1 shows, when considering real international oil prices back to 1861 the highest price was in 1864 so that if this price series were decomposed into p_{max}, p_{rec}, and p_{cut} then the maximum price, p_{max}, would have been constant since 1864 with increases in the 1970s early 1980s and the mid to late 2000s deemed merely as a price recovery, p_{rec}.[7] For the shorter data period, beginning in 1960 used in this paper the countries can be split into two groups. For nine of the 17 countries (Group A) the real energy price generally falls from the start of the period until the late 1970s / early 1980s; consequently the first notable jump in p_{max} is around this time (see Figure 2a and 3a). For the nine countries in Group A this suggests that the energy crisis of the early 1970s represented just a price recovery, p_{rec}. Yet, as Figure 4a shows, if the data starts in 1970 then the early 1970s is seen as a maximum price,

[7] We are grateful to an anonymous referee for suggesting the inclusion of Figures 1-4.

p_{max} for the nine Group A countries. Conversely, for the other eight counties (Group B) the early 1970s is seen as being as a maximum price, p_{max} whether the data starts in 1960 or 1970 (see Figures 2b, 3b and 4b).

Figure 2: Actual Price Data 1960 - 2008

Figure 2a: Group A

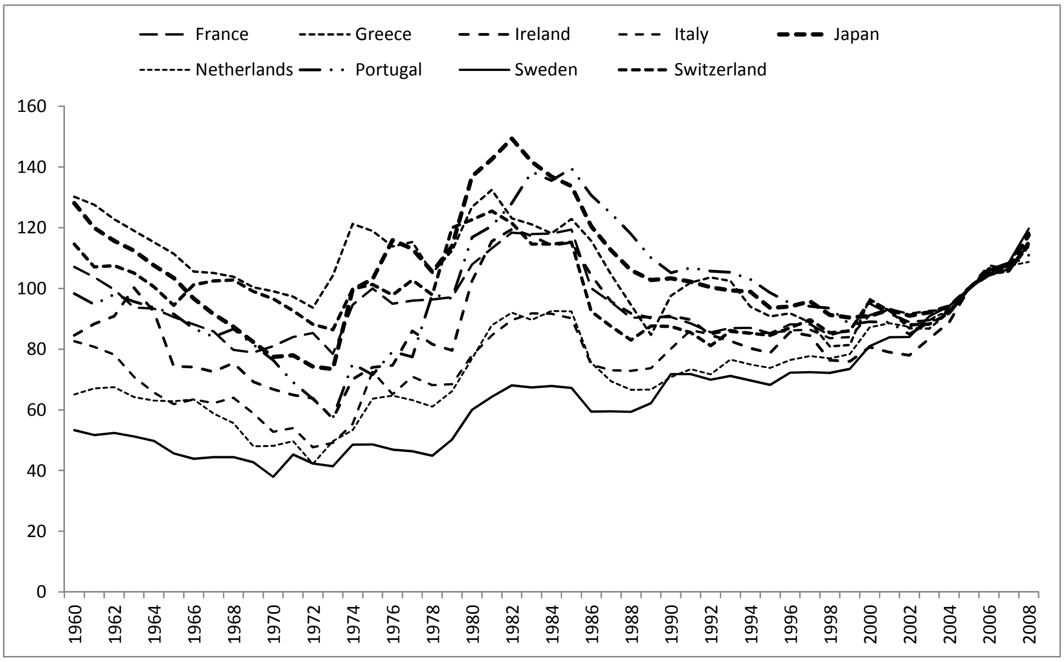


Figure 2b: Group B

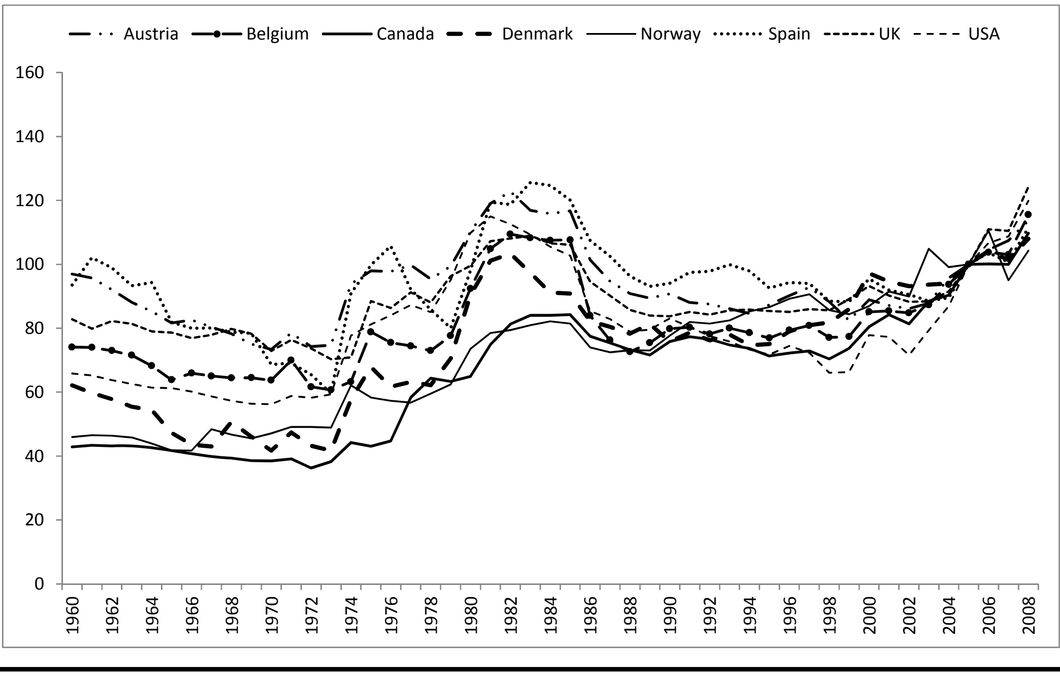


Figure 3: p_{max} for samples starting in 1960.

Figure 3a: Group A

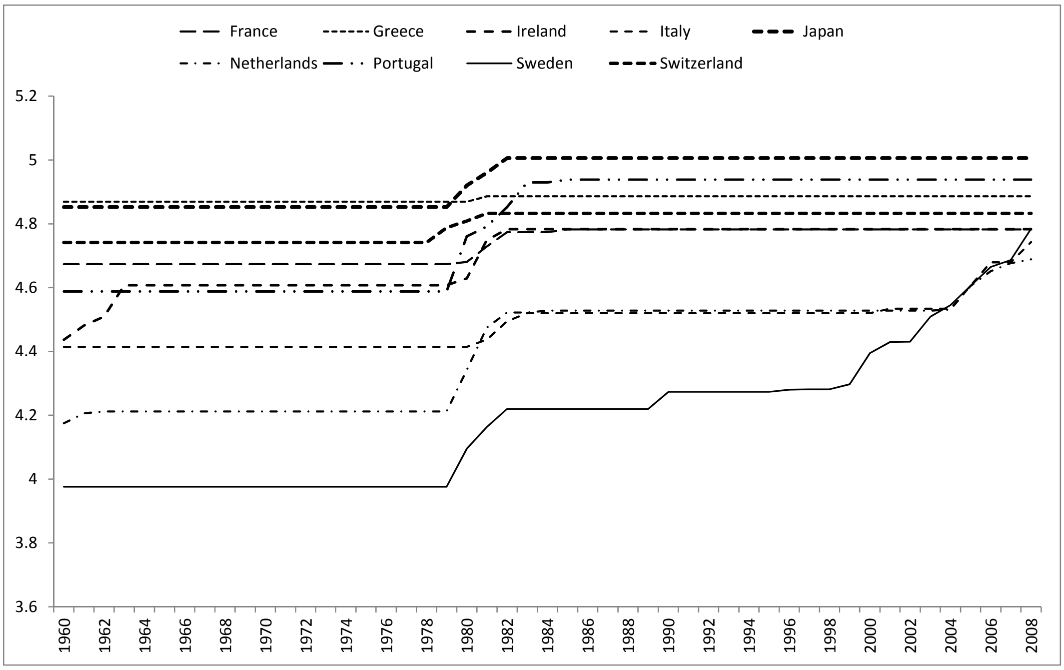


Figure 3b: Group B

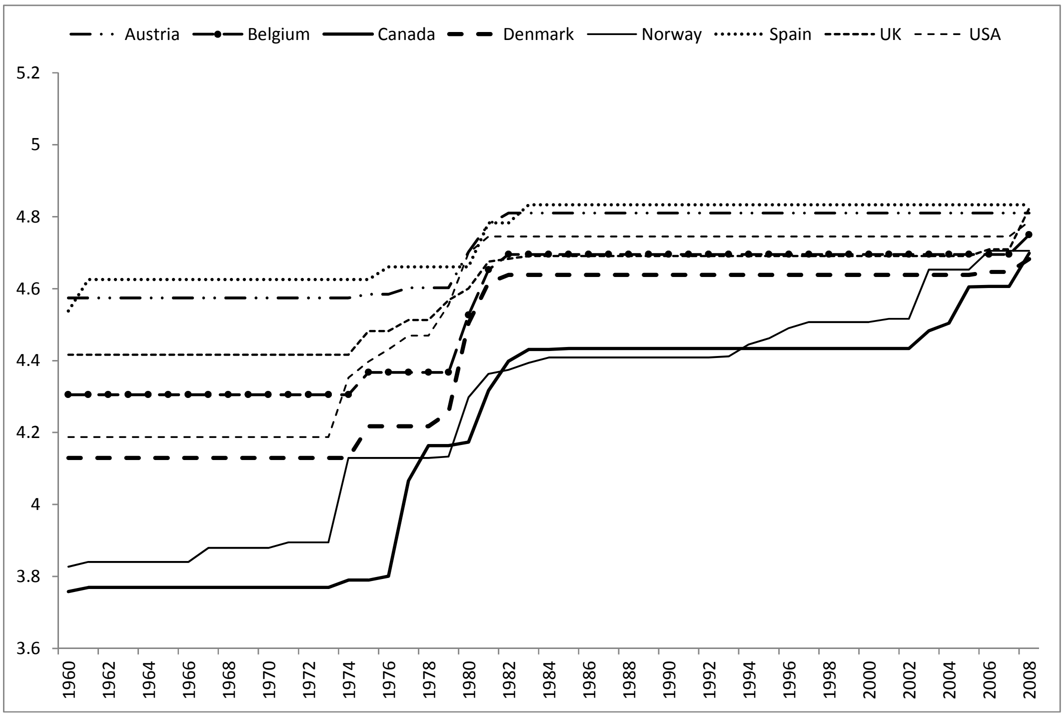


Figure 4: p_{max} **for samples starting in 1970.**

Figure 4a: Group A

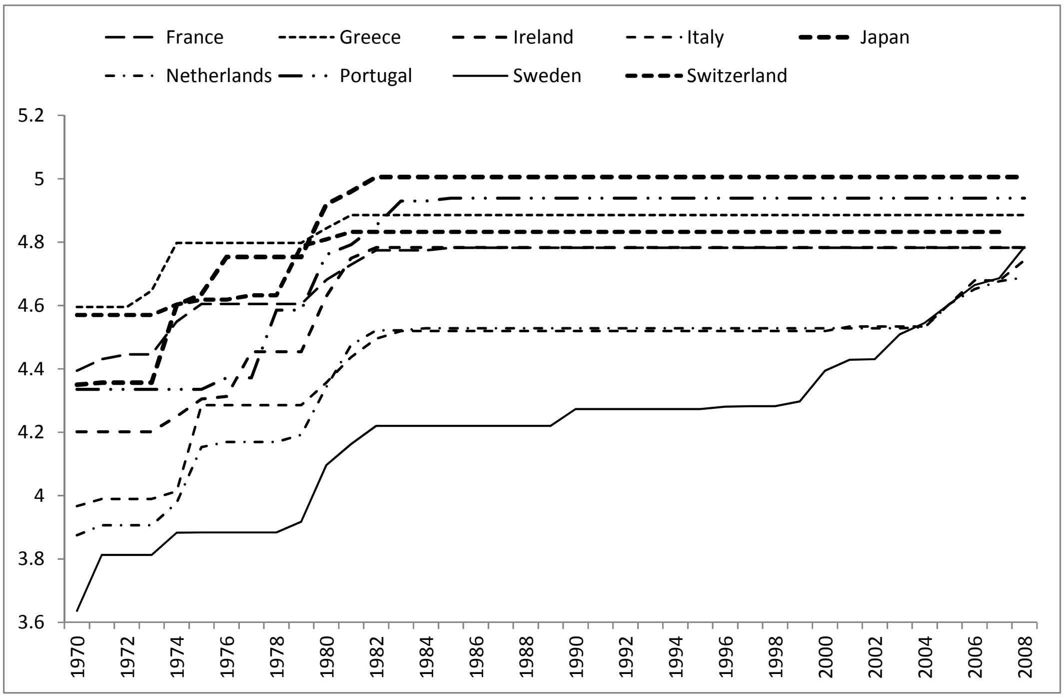
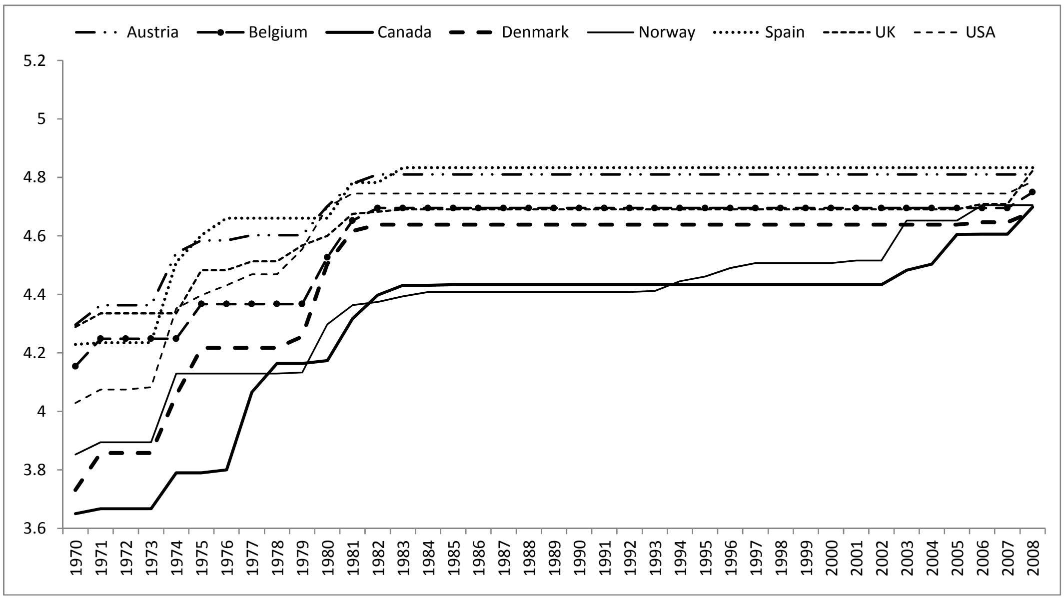


Figure 4a: Group B



This begs the question of exactly what is p_{max} attempting to measure. The idea being that it measures price shocks (based on a rise in the real price of energy above the previous maximum) is appealing in principle. However, can it be right that in one sample period the early 1970s energy price hike is seen as a shock when in others it is not? Since, everything that is known about that period suggests that it definitely was a shock. Moreover, it begs the additional question on how reliable and useful are estimated energy demand models based on the p_{max}, p_{rec}, and p_{cut} decomposition if events such as the early 1970s oil price shock are (arbitrarily) classified according to when the data period starts. This is what this paper attempts to explore.

In summary, although the APR model based on the p_{max}, p_{rec}, and p_{cut} decomposition has been widely used in estimating energy demand models, there are a number of criticisms of the approach. This paper therefore focuses on the key concern, that the estimates are dependent on the start date of the sample. In particular, various samples with different start and/or end dates are used to estimate models with APR based on the p_{max}, p_{rec}, and p_{cut} decomposition in order to examine the impact on the stability of the estimated energy demand responses.

3. Data

Data for 17 OECD countries (Austria, Belgium, Canada, Denmark, France, Greece, Ireland, Italy, Japan, The Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the UK and the US) are employed in this study. Per capita energy and per capita income for each country is calculated from data on aggregate energy consumption (ktoe) and GDP (billions 2000 US$ using PPP) and population from the IEA energy statistics database (www.iea.org) covering the period 1960 to 2008. The real price index (2000=100) series is obtained by splicing two series 1960-1980 (1972=100) and 1978-2008 (2000=100) together using the ratio from the overlap year 1978 The 1978-2008 energy prices are from the IEA database while energy prices from 1960-1980 came from an alternative source using each country's data as captured in Baade (1981), determined by weighing household and industrial gas, coal and electricity as well as diesel and kerosene by their fuel consumption shares.[8] The final panel data used is the natural logarithm forms of the per capita energy (E), per capita income (Y) and real energy price index (P).

The different sample periods for the estimation are obtained by drawing, from the 1960-2008 panel data, samples with different starting years from 1960 up to and including 1987 and for each sample re-calculating the decomposed price components (explained below). (Using

[8] This source was used in a similar way by Prosser (1985) and Adeyemi et al. (2010).

periods with starting years spanning 1960 to 1987 should capture the oil price increases, and by extension energy prices, of the 1970s and the low prices of the 1960s and mid-1980s to see how the starting year of a drawn dataset affects the stability of the estimated elasticities, whether it be high or low.) However, this can be done in two ways giving two types of datasets: one with fixed degrees of freedom [hereafter fixed-df] and one with varying degrees of freedom [hereafter varying-df]. The essence of generating these two datasets is to help identify any possible effect that the loss of degrees of freedom, in the different sample periods forming the varying-df dataset, has on the stability of the estimated energy demand response. The construction of these two possible datasets is as follows:

- **Varying-df**: The original 1960-2008 panel data is re-constructed by changing the starting years consecutively from 1960 to 1987, but maintaining the final year, 2008, for each sample period (i.e. 1960-2008, 1961-2008 and so on until 1987-2008) but each time re-calculating the decomposed price data.

- **Fixed-df**: In order to identify any possible effect of loss of degrees of freedom for the different estimation periods constructed above, another set of sampling periods are constructed but with a fixed 22 years included in each sample period.[9] So similar to the varying-df version, the original 1960-2008 panel data is re-constructed by changing the starting years consecutively from 1960 to 1987, but with a the 22 year period fixed so that the final year varies (i.e. 1960-1981, 1961-1982 and so on until 1987-2008) [10] and again re-calculating the decomposed price data for each sample.

Hence, there is a fixed-df and a varying-df dataset of estimation periods that are applied to the models described in the next section in order to analyse the stability of the estimated coefficients.[11]

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[9] 22 years were chosen in order to ensure that most of the sample periods included periods of rising and low oil prices. Although the 22 year estimation period might appear arbitrary and/or short, the use of panel data for 17 countries over a 22-year period still provides a total of 357 observations for estimation after allowing for the elimination of one year for each country due to the one year lag in the model.

[10] Similar to the varying-df the 1960 to 1987 starting dates are chosen in order to capture the periods of rising and low oil prices.

[11] Although this is analogous to undertaking 'recursive estimation' and 'rolling window' estimation, it is more comprehensive given a new data set is constructed for each new time period considered.

4. Methodology

The exposition of the estimated models is based on Adeyemi and Hunt's (2007) re-statement of the Gately and Huntington (2002) and Griffin and Schulman (2005) methodology. From a Koyck model, a general symmetric model is specified whereby the natural logarithm of per capita energy consumption (e_t) is dependent on the natural logarithm of real income per capita (y_t) and a distributed lag of the past natural logarithm of the real price of energy (p_t). This is mathematically represented as follows:

$$e_t = f[y_t, \gamma(L)p_t] \tag{1}$$

where L is the lag operator.

Assuming a linear specification and that the lag distribution on prices follows a geometric lag distribution, Eq. (1) can be written as:

$$e_t = \alpha + \beta y_t + \frac{\lambda p_t}{1 - \lambda L} + \mu_t \tag{2}$$

where μ_t is the random error term assumed to be $N(0, \sigma_t^2)$.

Eq. (2) can further be transformed by the lag operator, L to obtain:

$$e_t = \psi + \beta(y_t - \lambda y_{t-1}) + \gamma p_t + \lambda e_{t-1} + \varepsilon_t \tag{3}$$

where $\psi = \alpha(1 - \lambda)$ and $\varepsilon_t = \mu_t - \lambda \mu_{t-1}$.

However, given that a panel data of OECD countries is used, like Gately and Huntington (2002), Eq. (3) is re-written in a panel context and augmented with country dummies in order to allow for a different constant for each country, i, (the fixed effects approach) as given by:

$$e_{it} = \psi + \beta(y_{it} - \lambda y_{it-1}) + \gamma p_{it} + \lambda e_{it-1} + \delta_i D_i + \varepsilon_{it} \tag{4}$$

where $\varepsilon_{it} = \mu_{it} - \lambda\mu_{it-1}$[12] and δ_i represent the differential constants for the individual countries relative to the base constant ψ with all other parameters assumed to be constant across countries. Eq. (4) constitutes the general conventional symmetric price specification energy demand model using a Koyck-lag equation. In order to introduce APR into the initial model the price variable is decomposed as follows:

$$p_t = p_{max} + p_{rec} + p_{cut} \tag{5}$$

where

$p_{max,t} = max(p_1, \dots, p_t)$, representing the log of the maximum historical price

$p_{rec,t} = \sum_{t=1}^{t} max\{0, (p_t - p_{t-1}) - (p_{max,t} - p_{max,t-1})\}$, representing the cumulative sub-maximum increases in the logarithm of price, monotonically non-decreasing, $p_{rec,t} \geq 0$

$p_{cut,t} = \sum_{t=1}^{t} min\{0, (p_t - p_{t-1}) - (p_{max,t} - p_{max,t-1})\}$, increases in the logarithm of maximum historical price, monotonically non-decreasing, $p_{max,t} \geq 0$.[13]

The asymmetric model specification used by Gately and Huntington (2002), excluding the income asymmetry,[14] is obtained by substituting Eq. (5) into Eq. (4) and simplifying further to get what Adeyemi and Hunt (2007) refer to as Model I:

$$e_{it} = \psi + \beta(y_{it} - \lambda y_{it-1}) + \gamma_m p_{max,it} + \gamma_r p_{rec,it} + \gamma_c p_{cut,it} + \lambda e_{it-1} + \delta_i D_i + \varepsilon_{it} \tag{6}$$

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12 Gately and Huntington assumed in its preferred model specification that $\varepsilon_{it}$is not autocorrelated but independently and normally distributed, thus ignoring the first order moving average, MA(1) structure that comes about from the Koyck derivation (Adeyemi and Hunt, 2007). This issue also warrants further investigation.

13 Gately and Huntington (2002) include p_1 in their decomposition as follows:

$p_t = p_1 + p_{max} + p_{rec} + p_{cut}$, where the components are defined as follow:

p_1 = logarithm of price in the starting year, t=1

$p_{max,t} = \sum_{t=1}^{t}\{\max(p_1, \dots, p_t) - \max(p_1, \dots, p_{t-1})\}$, representing cumulative increases in the logarithm of maximum historical price, monotonically non-decreasing, $p_{max,t} \geq 0$. p_{rec} and p_{cut} have the same definition as those in the text above. This is slightly different to the decomposition used here given the focus on the effect of using samples with different starting years. The alternative was used in order to eliminate any influence on the estimated base constant term. The base constant term in Gately and Huntington (2002) is $\alpha(1-\lambda) + \gamma p_1$ but for the specification used here it is $\alpha(1-\lambda)$ as in Eq. (4)). It is important to note however that the estimated income, price elasticities are the same irrespective of which decomposition is used.

14 Gately and Huntington (2002) included asymmetric income responses in their model, but in general the statistical test for symmetry was not significant, indicating that income is symmetric and not asymmetric. The specified model therefore assumes symmetric income responses as used by Griffin and Schulman (2005).

where ψ and ε_{it} are as originally defined.

In setting up their model, Griffin and Schulman (2005) included a variable z_t in Eq. (1) to represent a technical index for energy efficiency. The revised equation therefore becomes:

$$e_t = f[y_t, \gamma(L)p_t, z_t] \tag{7}$$

When written in log-linear form this becomes

$$e_t = \alpha + \beta y_t + \frac{\lambda p_t}{1 - \lambda L} + \theta z_t + \mu_t \tag{8}$$

and transforming by the lag operator, L and simplifying further yields:

$$e_{it} = \psi + \beta(y_{it} - \lambda y_{it-1}) + \gamma p_{it} + \lambda e_{it-1} + \theta(z_t - \lambda z_{t-1}) + \varepsilon_{it} \tag{9}$$

Since z_t is unobservable, Griffin and Schulman (2005) replaced $\theta(z_t - \lambda z_{t-1})$ in Eq. (9) above with the simpler time dummies in the panel context to obtain Eq. (10) below; getting, what Adeyemi and Hunt (2007) refer to as, Model II:

$$e_{it} = \psi + \beta(y_{it} - \lambda y_{it-1}) + \gamma p_{it} + \lambda e_{it-1} + \delta_i D_i + \theta_t D_t + \varepsilon_{it} \tag{10}$$

where θ_t represents the differential time dummy coefficients for each year of the sample period relative to the base, ψ.

In order to compare their model with that of Gately and Huntington (2002), Griffin and Schulman (2005) also introduced time dummies into Eq. (6) to capture exogenous energy-saving technical progress; giving, what Adeyemi and Hunt (2007) refer to as, Model III:

$$e_{it} = \psi + \beta(y_{it} - \lambda y_{it-1}) + \gamma_{max} p_{max,it} + \gamma_{rec} p_{rec,it} + \gamma_{cut} p_{cut,it} + \lambda e_{it-1} + \delta_i D_i + \theta_t D_t + \varepsilon_{it} \tag{11}$$

In summary, the restricted models given by Eq. (6) and Eq. (10) and the unrestricted model given by Eq. (11) represent Models I, II and III respectively and can be used to estimate the coefficients of energy demand. Following Huntington (2006), simple F-tests of linear restrictions can be applied to test the restriction of imposing symmetry when moving from Model III to Model II (i.e. to test $H_0\colon \gamma_{max} = \gamma_{rec} = \gamma_{cut}$) and the restriction of removing the time dummies when moving from Model III to Model I (i.e. to test $H_0\colon \theta_t = 0$) in order to attempt to find the 'preferred specification'. (These tests were also explored by Adeyemi et al., 2010.)

In an attempt to provide empirical evidence to justify the criticism that specifications with APR, via the p_{max}, p_{rec}, and p_{cut} decomposition technique, are conditional on the time period over which the data is drawn, Griffin and Schulman (2005) did partially consider the stability hypothesis using two sample periods one for 1970-1996 and one for 1960-1999. However, this did not fully address the issue and arguably a more systematic approach of investigating the stability of the estimated coefficients for different sample periods over time is appropriate. The more systematic approach employed in this paper is therefore achieved by initially estimating Models I and III using the different sample periods as outlined above. This allows the stability (or otherwise) of the estimated energy demand responses to be observed across the different sample periods. These are then compared to the estimates of the symmetrical Model II where any instability of the estimates is due purely to the different sample periods, ***not*** because of the need to re-calculate the decomposed price data over the different periods (as is necessary for the asymmetrical Models I and III). [15] In addition, the Huntington (2006) tests outlined above for the different sample periods are also undertaken to assess their stability (or otherwise). The results of this exercise are discussed in the next section.

[15] In other words, investigating the stability of Model II is no different to investigating the stability of the estimates in any model using 'recursive' or 'rolling window' estimation given a new data set does not need to be constructed. In contrast, as already stated, investigation of the stability of Models I and III does require the construction of a new data set for each period but is still similar to 'recursive' or 'rolling window' estimation.

5. Results

The results from estimating Models I and III using the different sample periods for the varying-df and fixed-df versions of the data are presented in Figures 5-8.[16] Figures 5 and 6 present the results of the models with APR but without time dummies (i.e. Model I, the Gately and Huntington, 2002 approach) for varying-df and fixed-df respectively. Figures 7 and 8 present the results of the models with APR but with time dummies (i.e. Model III, the Griffin and Schulman, 2005/Huntington, 2006 approach) for varying-df and fixed-df respectively. For all four figures: a, presents income response; b, presents the p_{max}, response; c, presents the p_{rec} response; and d, presents the p_{cut} response.

For Model I using the both the varying-df and fixed-df samples, (Figures 5a and 6a) it can be seen that income is always significantly different from zero. For Model I, using varying-df (Figures 5b, 5c, and 5d), all the asymmetric price components are significantly different from zero other than for a couple of periods in the early to mid-1980s. However, for the fixed-df samples for Model I (Figures 6b, 6c and 6d). the asymmetric price components are often not significantly different from zero.[17] For Model III it can be seen that income is always significantly different from zero (Figures 7a and 8a) while the asymmetric price components are often not significantly different from zero (Figures 7b-7d and 8b-8d). Furthermore, although the instability of all the estimated coefficients (Figures 5-8) is not as big as expected *a-priori*, there appears to be a relatively large variation.

[16] Note, that given the Koyck lag structure the first observation is lost from each data set. Therefore, the x-axis on these charts refers to the 'estimation periods' not the 'data set periods'.

[17] The spikes in the estimated p_{max}, coefficients for the data period starting 1980 (Figures 5b, 6b, 7b, and 8b) might be due to the second oil price shock which was initiated by the 1979 Iranian revolution, which was further worsened by the Iran-Iraq War in September 1980.

Figure 5: Model I, APR without Time Dummies with Varying-df

Figure 5a: Income Coefficient Series

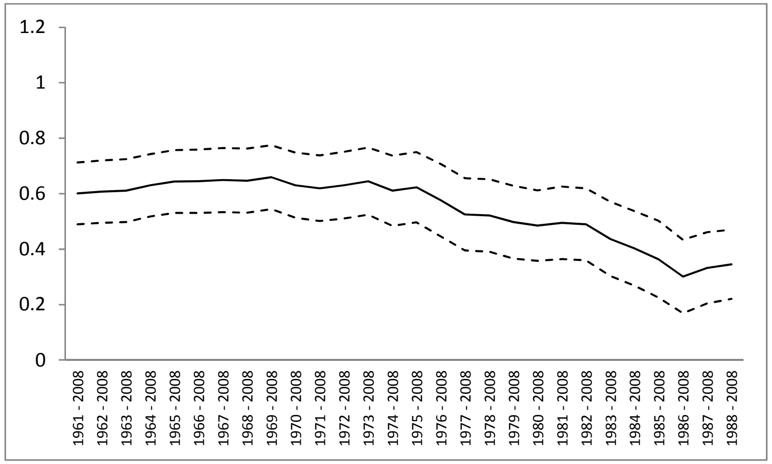


Figure 5b: Coefficient of Maximum Historical Price Series

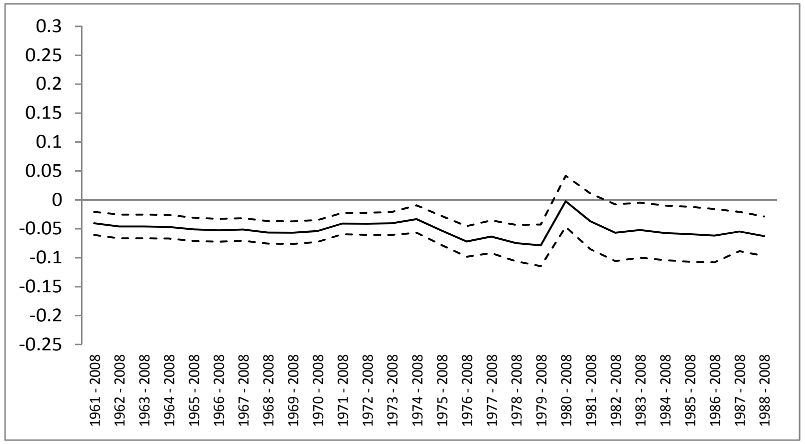


Figure 5c: Coefficient of Price Recovery Series

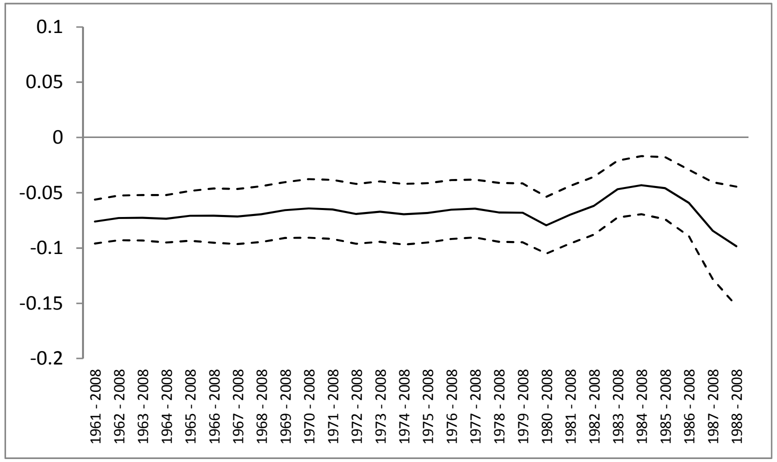
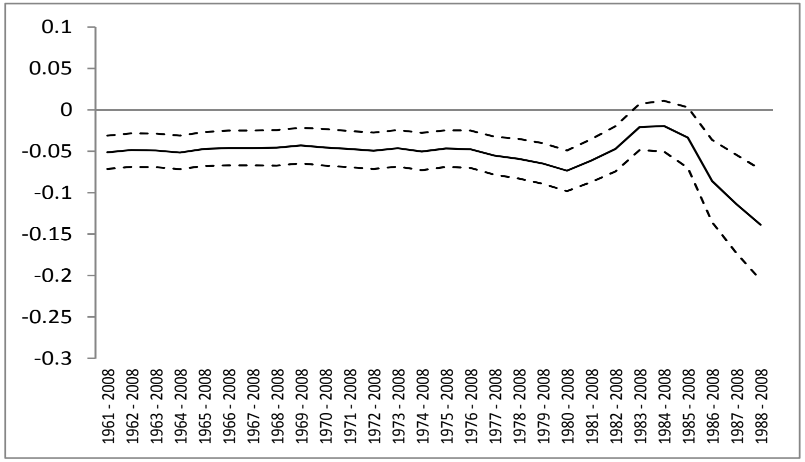


Figure 5d: Coefficient of Price Cut Series



Note: Measures are estimated elasticities and the upper and lower bounds are 95% confidence intervals. The x-axis refers to the 'estimation periods' rather than the 'data set periods'.

Figure 6: Model I, APR without Time Dummies with Fixed-df

Figure 6a: Income Coefficient Series

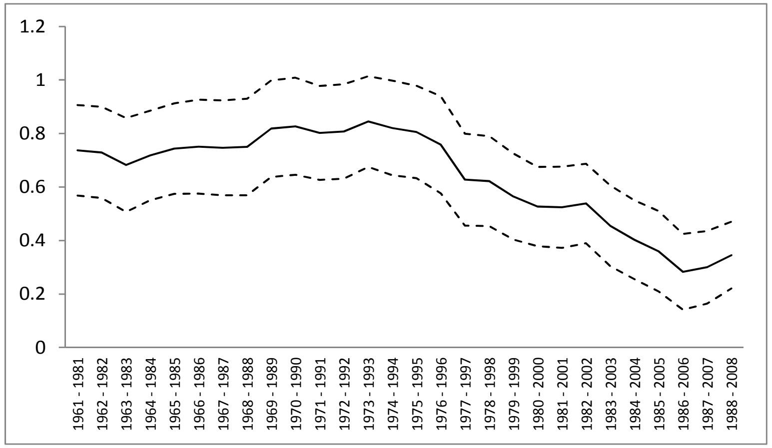


Figure 6b: Coefficient of Maximum Historical Price Series

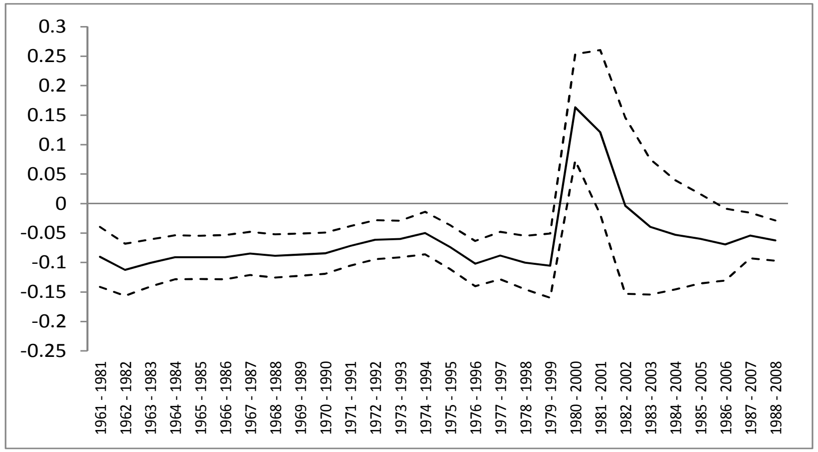


Figure 6c: Coefficient of Price Recovery Series

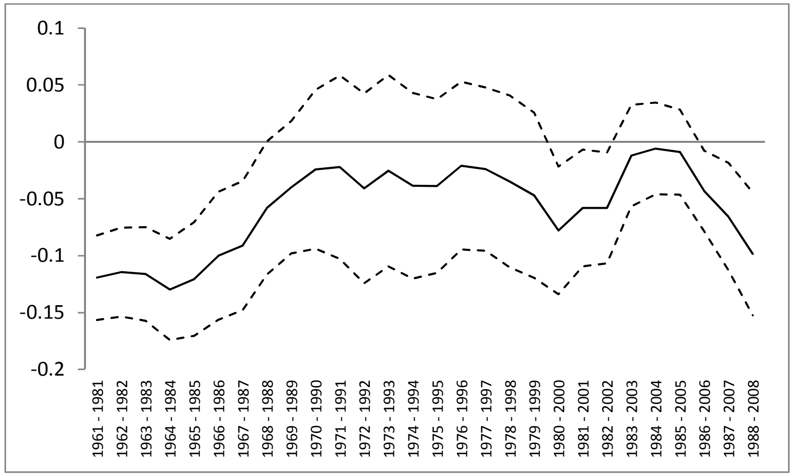
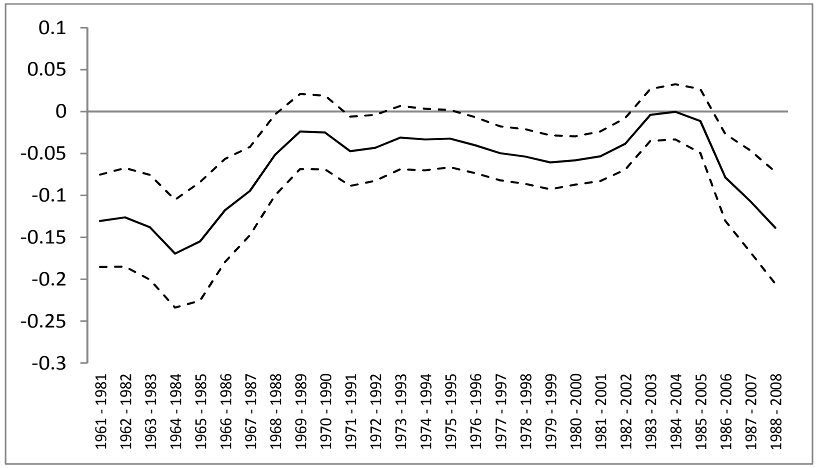


Figure 6d: Coefficient of Price Cut Series



Note: Measures are estimated elasticities and the upper and lower bounds are 95% confidence intervals. The x-axis refers to the 'estimation periods' rather than the 'data set periods'.

Figure 7: Model III, APR with Time Dummies with Varying-df

Figure 7a: Income Coefficient Series

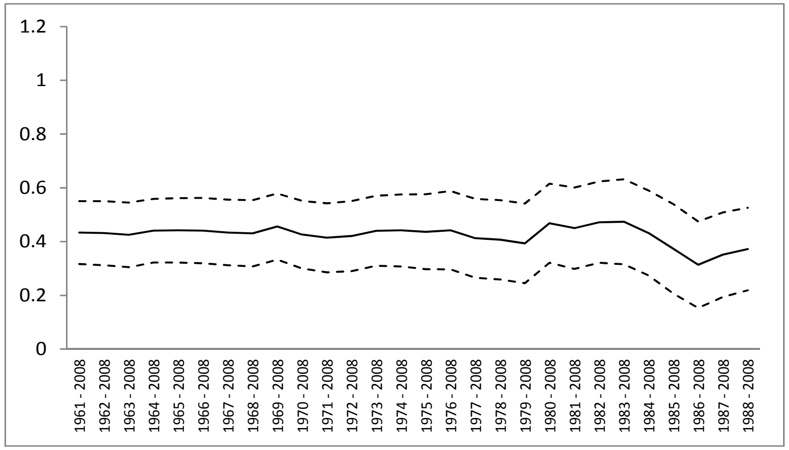


Figure 7b: Coefficient of Maximum Historical Price Series

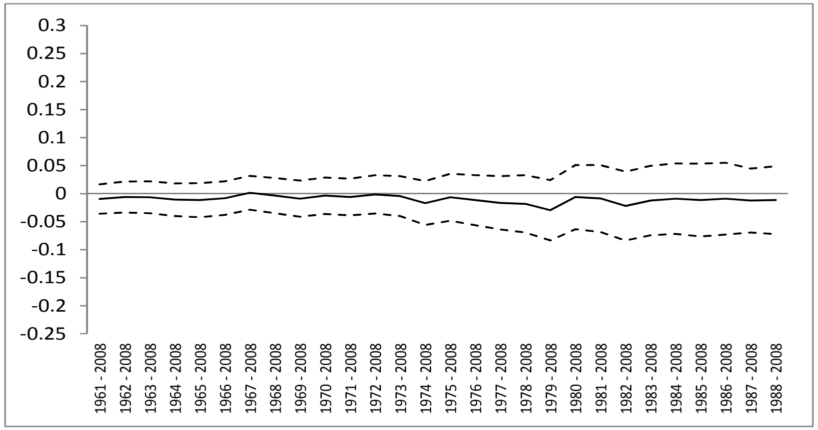


Figure 7c: Coefficient of Price Recovery Series

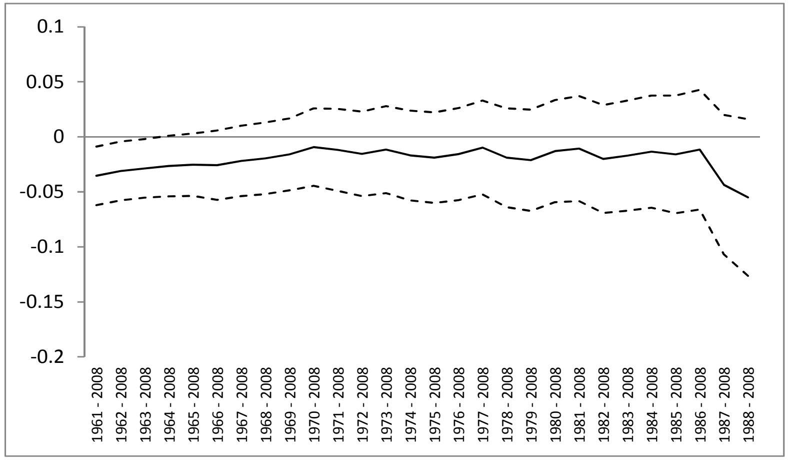
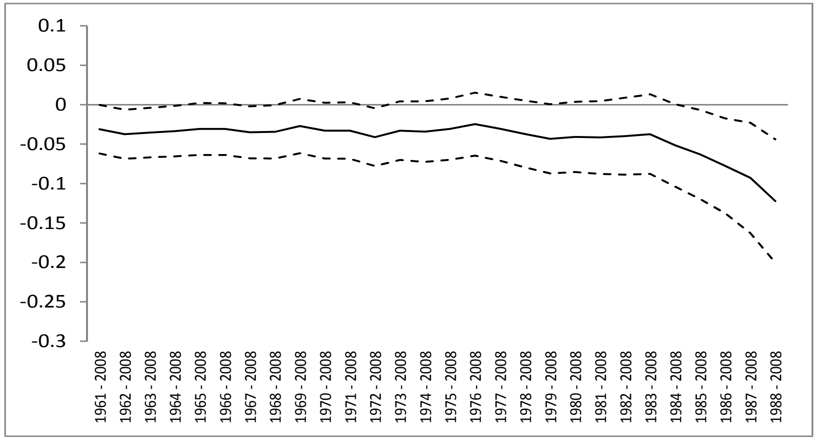


Figure 7d: Coefficient of Price Cut Series



Note: Measures are estimated elasticities and the upper and lower bounds are 95% confidence intervals. The x-axis refers to the 'estimation periods' rather than the 'data set periods'.

Figure 8: Model III, APR with Time Dummies with Fixed-df

Figure 8a: Income Coefficient Series

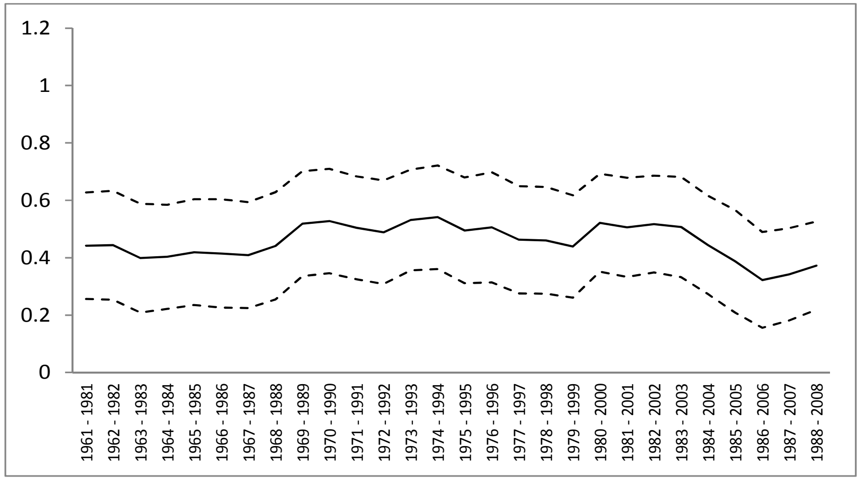


Figure 8b: Coefficient of Maximum Historical Price Series

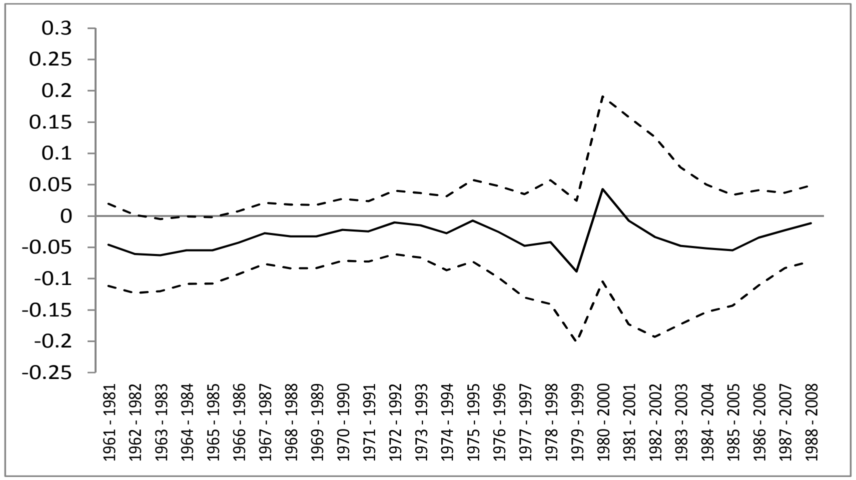


Figure 8c: Coefficient of Price Recovery Series

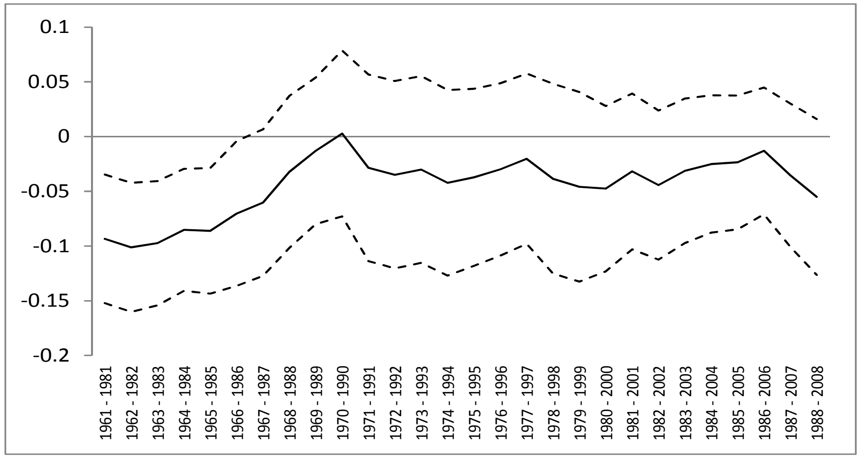
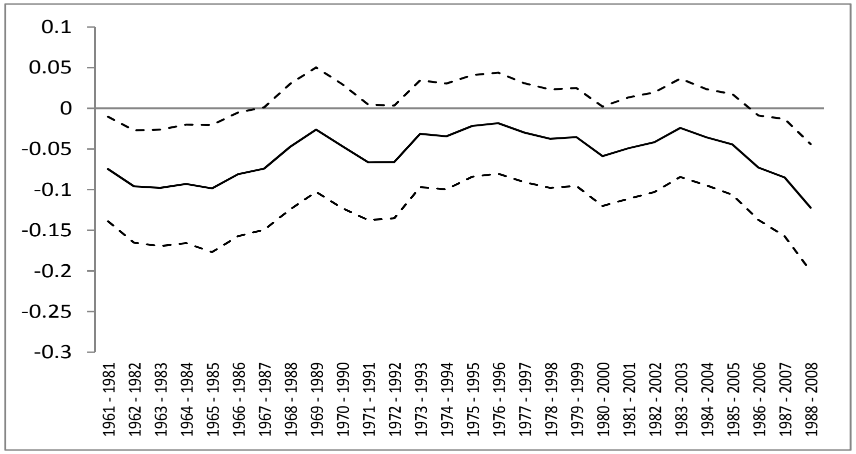


Figure 8d: Coefficient of Price Cut Series



Note: Measures are estimated elasticities and the upper and lower bounds are 95% confidence intervals. The x-axis refers to the 'estimation periods' rather than the 'data set periods'.

To explore the stability further (and compare across models and different data samples) Figure 9 presents the estimated income coefficients across all models and data sets (including Model II[18]). This shows that Model I, for both varying-df and fixed-df, shows the greatest variation. This is also illustrated in Table 1 showing that the income elasticity estimates ranges from 0.3 to 0.7 for varying-df and from 0.3 to 0.8 for fixed-df, however for Model III the variation is less, 0.3 to 0.5 for both varying-df and fixed-df. The range for Model II is similar to Model III; 0.4 to 0.5 for both varying-df and fixed-df. However, the degree of variation is slightly less. The Coefficient of Variation (CoV) for Model III is 8% for varying-df and 13% for fixed-df compared to the 6% for varying-df and 11% for fixed-df for Model II; both of which are less than Model I, the CoV being 20% for varying-df and 27% for fixed-df. This is further seen in Figure 9, which also illustrates the similarity between estimated income coefficients from Model III and Model II. In fact, the Model III and Model II estimates are very similar for the varying-df and the fixed-df, suggesting that when time dummies are included, the estimated income coefficient does not noticeably vary whether the price variable is decomposed or not. In summary, it would appear that the different sample periods do impact on the stability of the estimated income coefficient, with the variation generally being greater than the normal time series variation found for Model II, nevertheless, the impact appears to be less when time dummies are included.

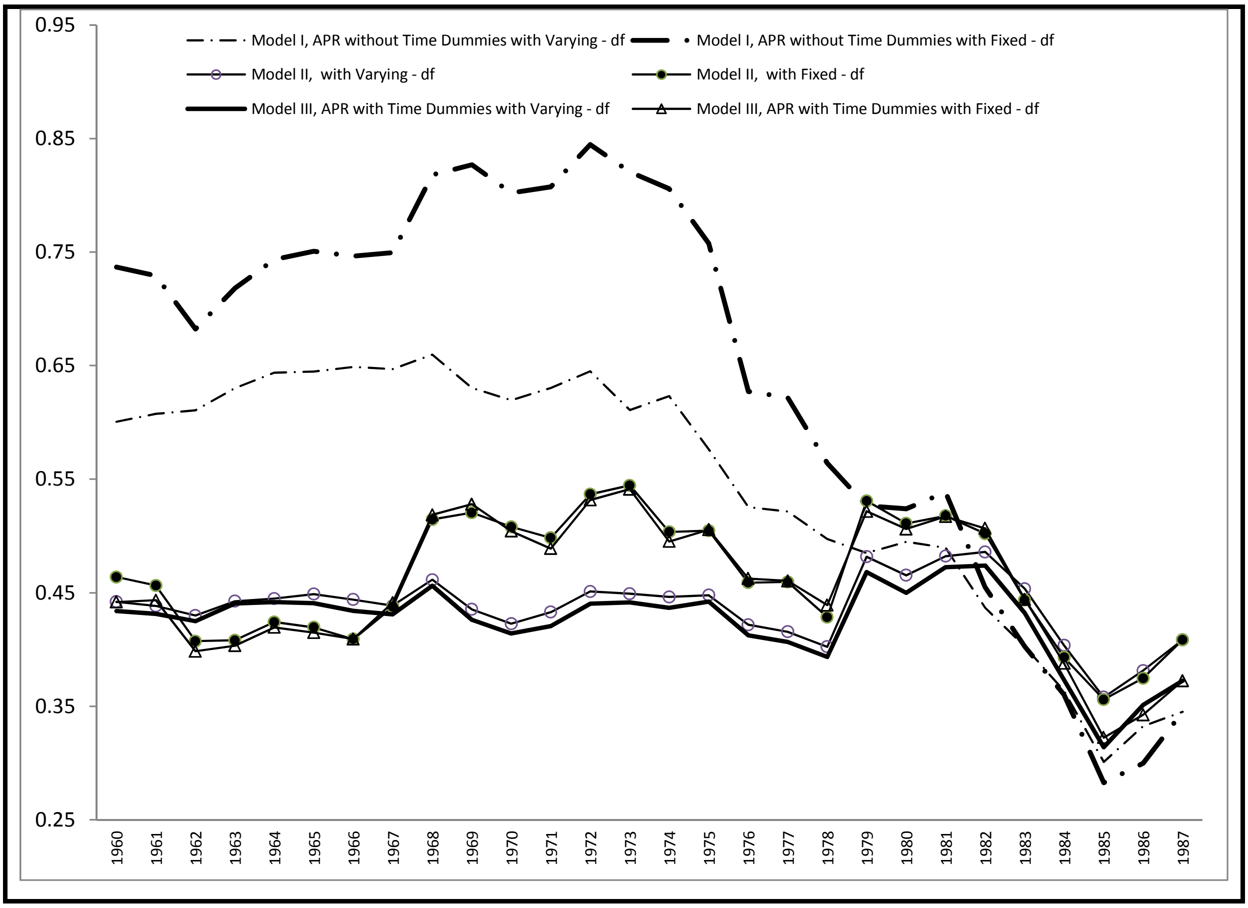
Figure 10 presents the estimated price coefficients across all models and data sets, including Model II (Figure 10a presents the p_{max}, coefficients from Models I and III; Figure 10b the p_{rec} coefficients from Models I and III; Figure 10c the p_{cut} coefficients from Models I and III; and Figure 10d the p coefficients from Model II). This suggests that the variation is greater for the decomposed price coefficients in Models I and III than the price coefficients in Model II. This is also illustrated in Table 1 where for the ranges of the price coefficient estimates for Model II and the CoV are on the whole lower than that for the decomposed price coefficients and the CoV in Models I and III. Again this would appear to indicate that the variation in estimated decomposed price coefficients in Models I and III is generally greater than the normal time series variation found in Model II.

[18] The values of the coefficients and their associated 95% confidence intervals for Model II are given in Figure A1 (for varying-df) and Figure A2 (for fixed-df) in Appendix A.

Table 1: Summary of estimated income and price coefficients.

	Model I		Model III		Model II	
	Varying-df	**Fixed-df**	**Varying-df**	**Fixed-df**	**Varying-df**	**Fixed-df**
Income Coefficient (y):						
Min	0.30	0.28	0.31	0.32	0.36	0.36
Max	0.66	0.84	0.47	0.54	0.49	0.54
Mean	0.54	0.64	0.42	0.46	0.44	0.46
Median	0.60	0.72	0.43	0.45	0.44	0.46
SD	0.11	0.17	0.04	0.06	0.03	0.05
CoV	20%	27%	8%	13%	6%	11%
Maximum Historical Price Coefficient (p_{max}): γ_{max}						
Min	-0.08	-0.11	-0.03	-0.09		
Max	0.00	0.16	0.00	0.04		
Mean	-0.05	-0.06	-0.01	-0.03		
Median	-0.05	-0.08	-0.01	-0.03		
D	0.01	0.06	0.01	0.02		
CoV	28%	101%	63%	71%		
Price Recovery Coefficient (p_{rec}): γ_{rec}						
Min	-0.10	-0.13	-0.06	-0.10		
Max	-0.04	-0.01	-0.01	0.00		
Mean	-0.07	-0.06	-0.02	-0.04		
Median	-0.07	-0.05	-0.02	-0.04		
SD	0.01	0.04	0.01	0.03		
CoV	16%	65%	50%	60%		
Price Cut Coefficient (p_{cut}): γ_{cut}						
Min	-0.14	-0.17	-0.12	-0.12		
Max	-0.02	0.00	-0.02	-0.02		
Mean	-0.05	-0.07	-0.04	-0.06		
Median	-0.05	-0.05	-0.04	-0.05		
SD	0.02	0.05	0.02	0.03		
CoV	43%	69%	49%	48%		
Price Coefficient (p): γ						
Min					-0.06	-0.08
Max					-0.02	-0.02
Mean					-0.03	-0.04
Median					-0.02	-0.04
SD					0.01	0.02
CoV					37%	39%

Figure 9: Comparison of estimated income coefficient for Models I, II, III.



Note: To allow for a comparison the x-axis refers to the start of the of the data period used for estimation. Therefore, for estimates with varying-df the end date of each of the series estimates is 2008 whereas for estimates with fixed-df the end date of each of the series estimates is 22 years after the start date shown.

Figure 11 illustrates the results from testing for symmetry in both Models I and Model III (i.e. testing $H_0: \gamma_{max} = \gamma_{rec} = \gamma_{cut}$). Figure 11a shows that for the varying-df estimates of Model I the null hypothesis of symmetry is generally rejected for the earlier data periods starting before 1970 (when, as seen in the introduction, the early 1970s energy crisis is regarded as just a price recovery for nine of the 17 countries in the sample). However, for the data sets starting from 1970 onwards in the majority of cases, the null hypothesis of symmetry cannot be rejected for Model I; which is similar to the results to the fixed-df results for all the periods. For Model III however, shown in Figure 11b, in almost all cases for all periods the null hypothesis of symmetry cannot be rejected; suggesting that Model II is favoured (statistically) to Model III. A result that is very stable across all estimation periods considered.

Figure 10: Comparison of estimated price coefficient for Models I, II, III.

Figure 10a: Coefficient of Maximum Historical Price Series

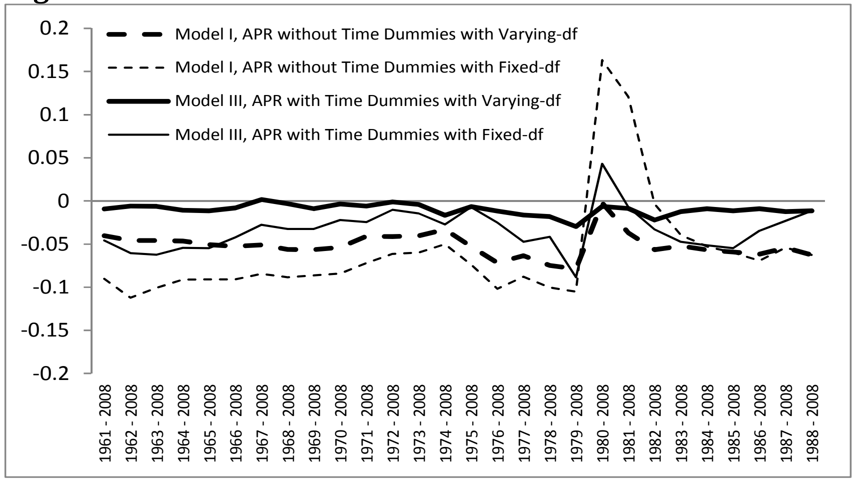


Figure 10b: Coefficient of Price Recovery Series

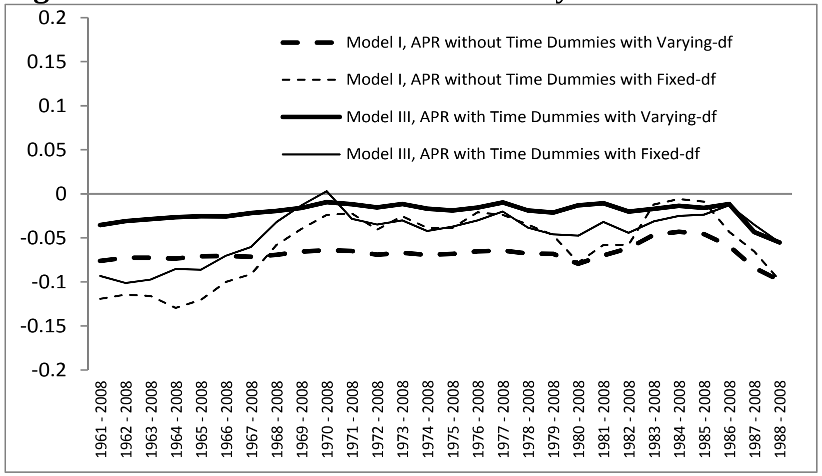


Figure 10c: Coefficient of Price Cut Series

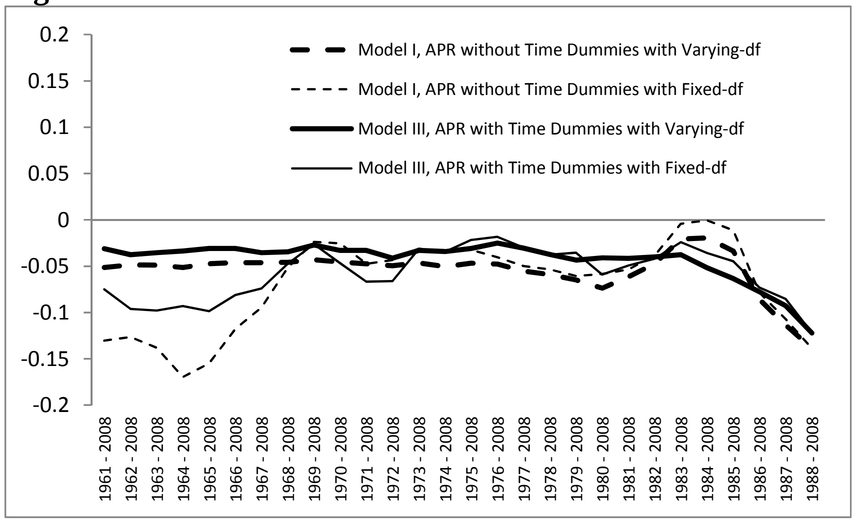
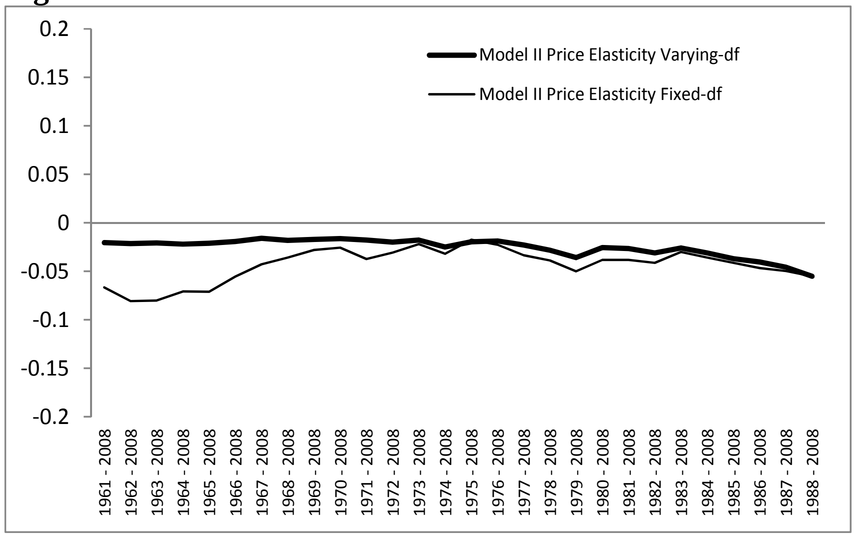


Figure 10d: Model II Coefficient of Price Series



Note: To allow for a comparison the x-axis refers to the start of the of the data period used for estimation. Therefore, for estimates with varying-df the end date of each of the series estimates is 2008 whereas for estimates with fixed-df the end date of each of the series estimates is 22 years after the start date shown.

Figure 11: Probabilities from Symmetry tests III ($H_0: \gamma_{max} = \gamma_{rec} = \gamma_{cut}$)

Figure 11a: Model I

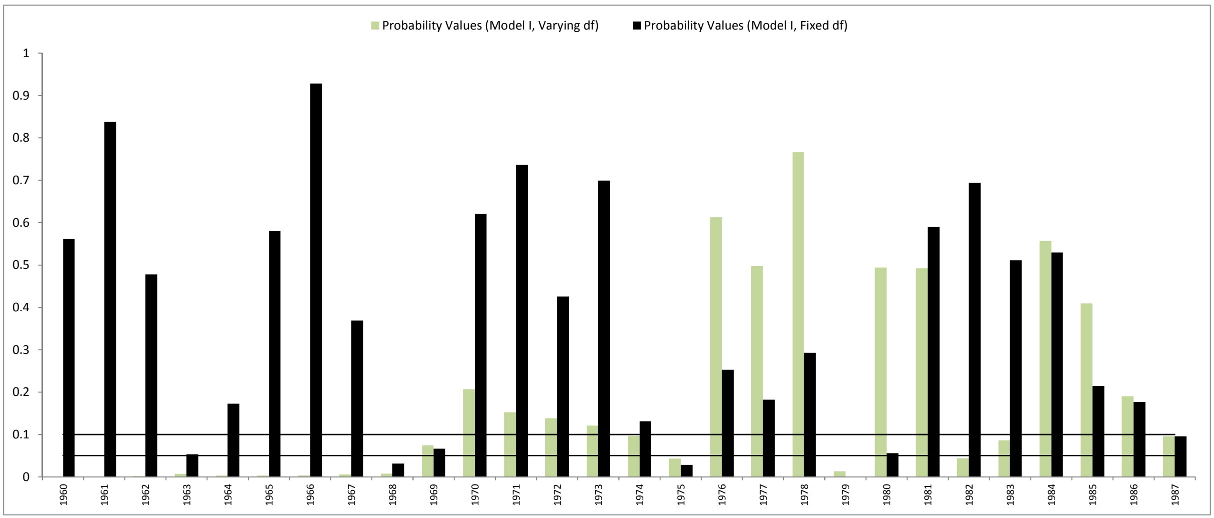
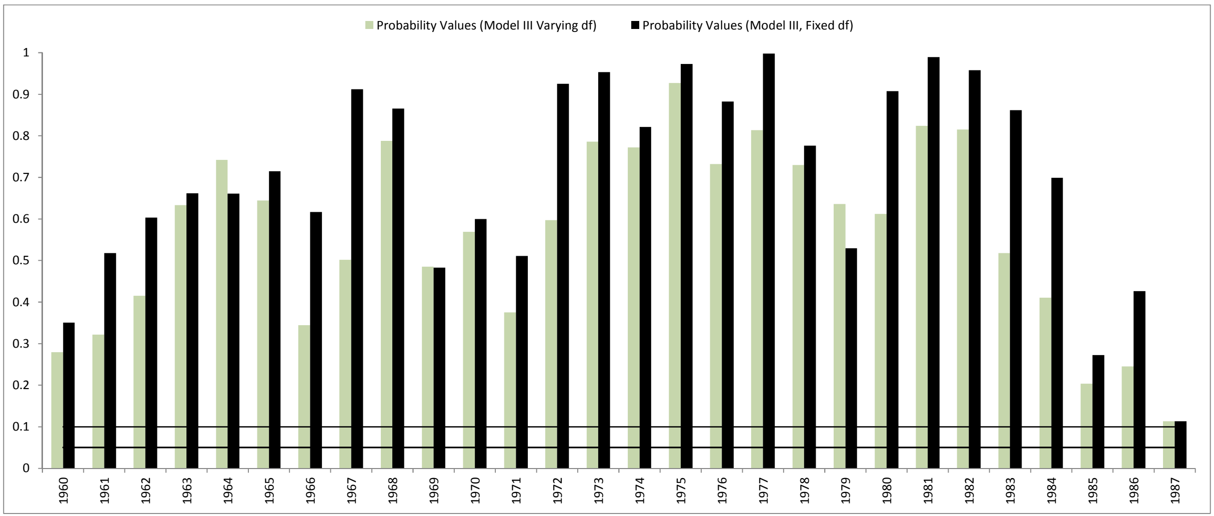


Figure 11b: Model III



Note: Horizontal lines show the 5% and 10% probabilities respectively. To allow for a comparison the x-axis refers to the start of the of the data period used for estimation. Therefore, for estimates with varying-df the end date of each of the series estimates is 2008 whereas for estimates with fixed-df the end date of each of the series estimates is 22 years after the start date shown.

For completeness, the tests of omitting the time dummies (i.e. testing $H_0: \theta_t = 0$) were conducted and in all cases for Models II and III using both varying-df and fixed-df the null hypothesis was rejected (with a probability of 0.00). Figures 12a and 12b show that for Model III the estimated coefficients for the time dummies are stable across the different estimation periods for both the varying-df and fixed-df. Moreover, these are very similar to those obtained for Model II shown in Figures 12c and 12b; however, the spread of the estimated time dummy coefficients for Model III appears slightly wider than that for Model II.

Finally, it is interesting to see the relationship between the coefficients of p_{max}, p_{rec}, and p_{cut} over the different estimation periods (shown in Figure 13). It is expected *a-priori* that in absolute terms the estimated p_{max}elasticity would be greater than or equal to the estimated p_{rec} elasticity which in turn would be greater than or equal to the estimated p_{cut}elasticity (i.e. $|\widehat{\gamma_{max}}| \geq |\widehat{\gamma_{rec}}| \geq |\widehat{\gamma_{cut}}|$). Or generally the estimated coefficient for p_{max} should be less than the estimated coefficient for p_{rec} which in turn should be less than or equal to estimated coefficient. However, Figure 13 shows that this is rarely the case for both Model I and Model III for both varying-df and fixed-df.

6. Summary and Conclusion

The price decomposition that separately measure the impact of prices above the previous maximum, a price recovery below the previous maximum and a price cut when modelling energy demand has been criticised as being sensitive to the time period sampled. This paper analyses this criticism in a systematic way by reconstruction the price decomposition terms (p_{max}, p_{rec}, and p_{cut}) for various data periods and estimating the Gately and Huntington (2002) and Griffin and Schulman (2005) models for each sample period. Although the variation is not as great as expected *a-priori*, the parameter estimates for the different sample periods do vary somewhat for the asymmetric models, whereas the parameter estimates do not vary so much for the symmetric model without a decomposed price variable; thus suggesting that the symmetric model will give more stable and reliable results. The analysis presented here therefore gives support to the argument put forward by Griffin and Schulman (2005).

Figure 12: Time Dummy Coefficients

Figure 12a: Model III with Varying-df

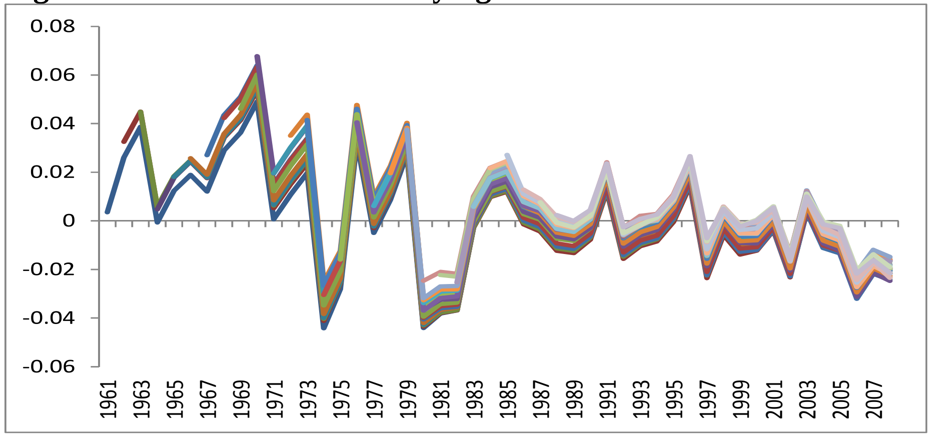


Figure 12b: Model III with Fixed-df

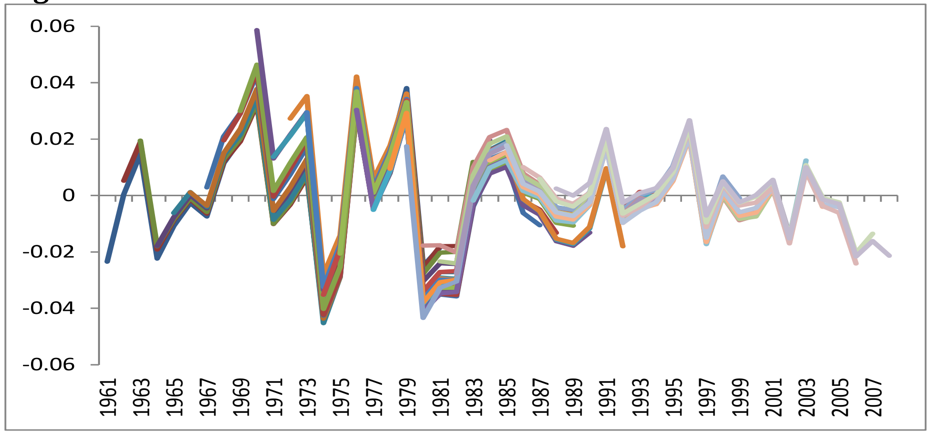


Figure 12c: Model II with Varying-df

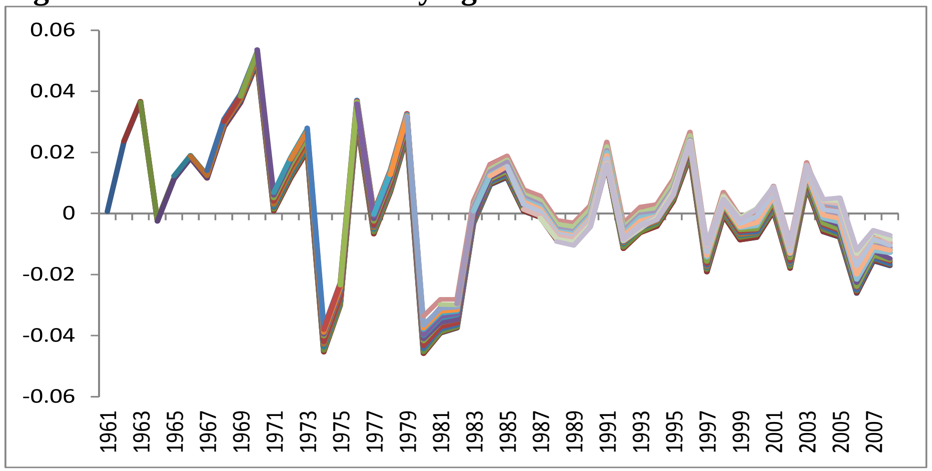
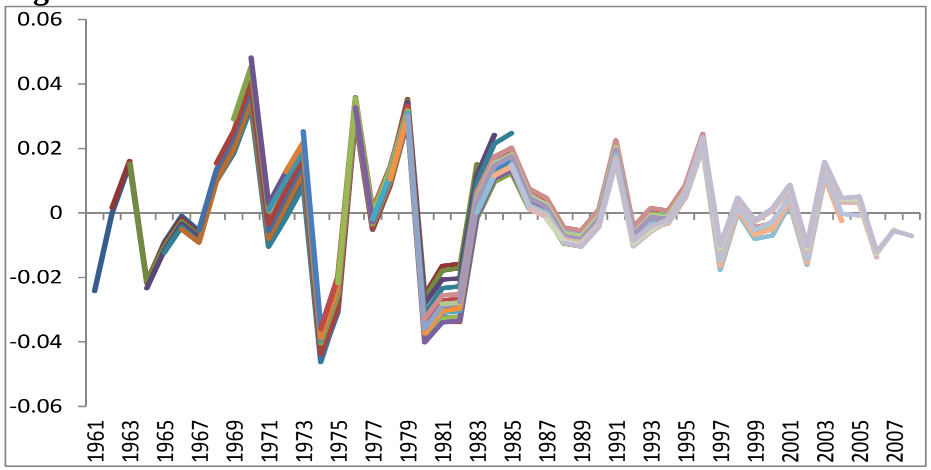


Figure 12d: Model II with Fixed-df



Note: Unlike other charts in this paper, the years on the x-axis refers to the year of the estimated time dummy coefficients.

Figure 13: Price Coefficient Comparisons

Figure 13a: Model I APR without Time Dummies with Varying-df

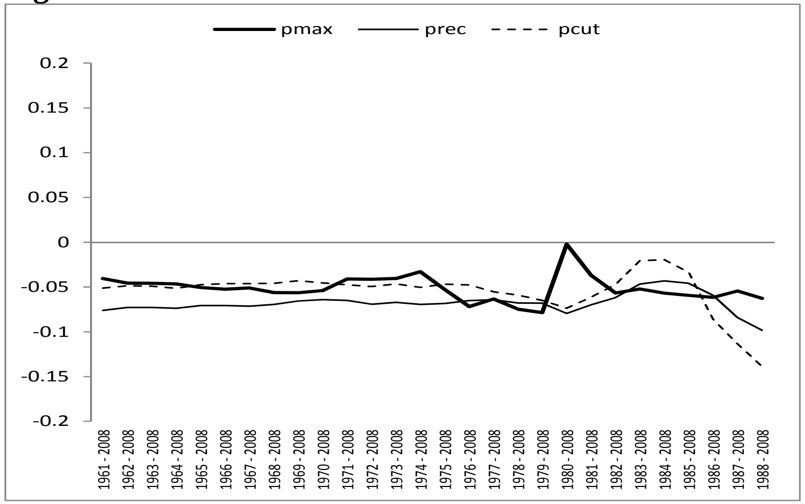


Figure 13b: Model I APR without Time Dummies with Fixed-df

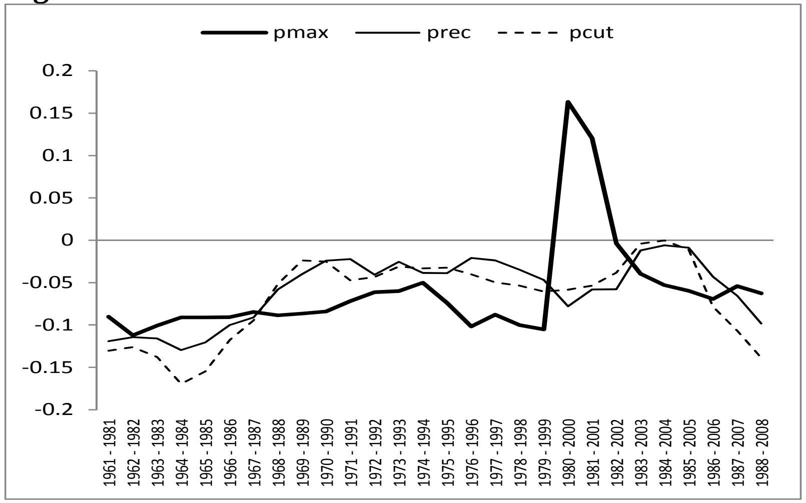


Figure 13c: Model III APR with Time Dummies with Varying-df

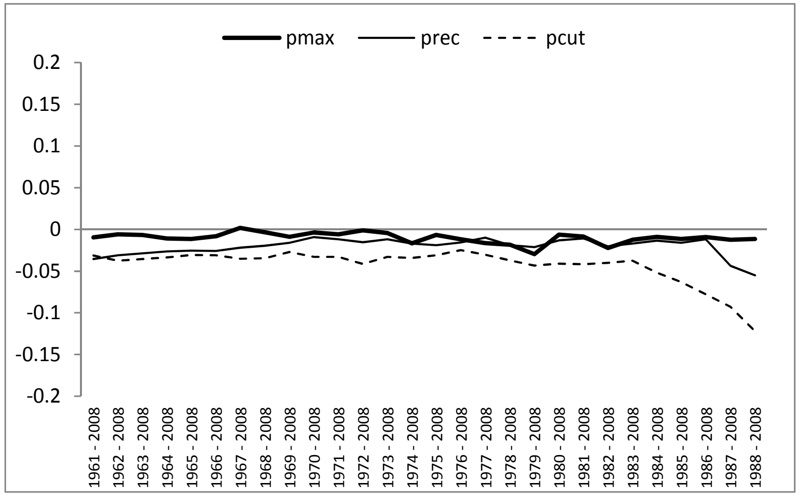
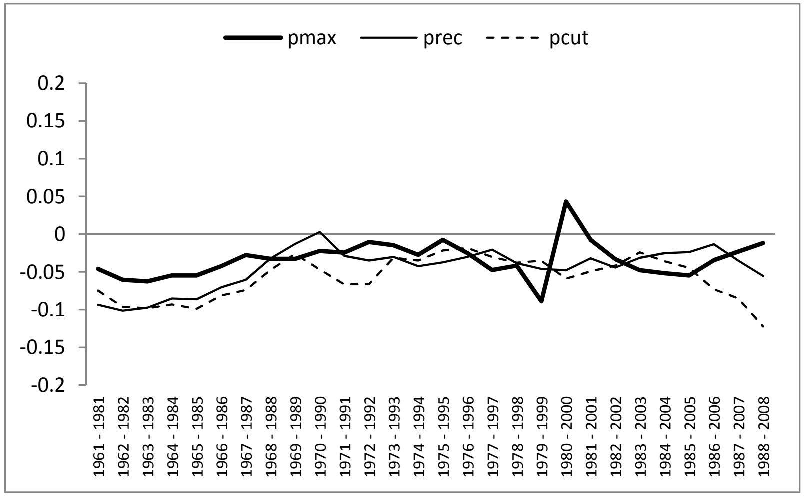


Figure 13d: Model III APR with Time Dummies with Fixed-df



Note: The x-axis refers to the 'estimation periods' rather than the 'data set periods'.

The findings of this analysis point to two lines of future enquiry, to further investigate the robustness of our results to i) different datasets and ii) alternative price decompositions. Therefore, it would be interesting to see the exercise repeated for different panel data sets to ascertain whether there is a dataset for which the results found here do not hold, such as that used in Dargay and Gately (2010). Moreover, it would also be useful to see whether an alternative decomposition to the p_{max}, p_{rec}, and p_{cut} version employed in this analysis would also suggest that on the grounds of stability the symmetric model is preferred to the asymmetric model. Hence, it would be interesting to see further work that conducts a similar exercise to that here, but with alternative price decompositions. Two possibilities are those used by Ryan and Plourde (2002a) and Frondel and Vance (2013), both of which do not require a new data set to be constructed for each period, and consequently are less likely to suffer from some of the problems seen with the p_{max}, p_{rec}, and p_{cut} decomposition. A fuller understanding of the robustness of our results with respect to the dataset and price decomposition would help ascertain whether the symmetric model is more stable and hence preferred *per se* or whether in fact there is an alternative price decomposition that is better at capturing APR which produces more stable and reliable estimates than the symmetric model.

Appendix A: Model II results

The results from estimating Model II using the different sample periods for the varying-df and fixed-df versions of the data are presented in Figure A1 and Figure A2; i.e. the results for the symmetric model with time dummies (i.e. the Griffin and Shulman, 2005 approach). These show that the coefficients for both the estimated price and income response are relatively stable.

Figure A1: Model II, Symmetric Price Response with Time Dummies with Varying-df (coefficients and 95% confidence intervals)

Figure A1a: Income

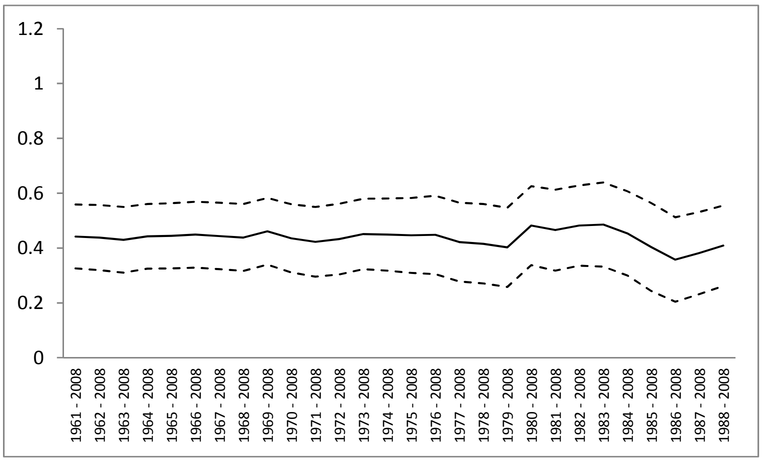
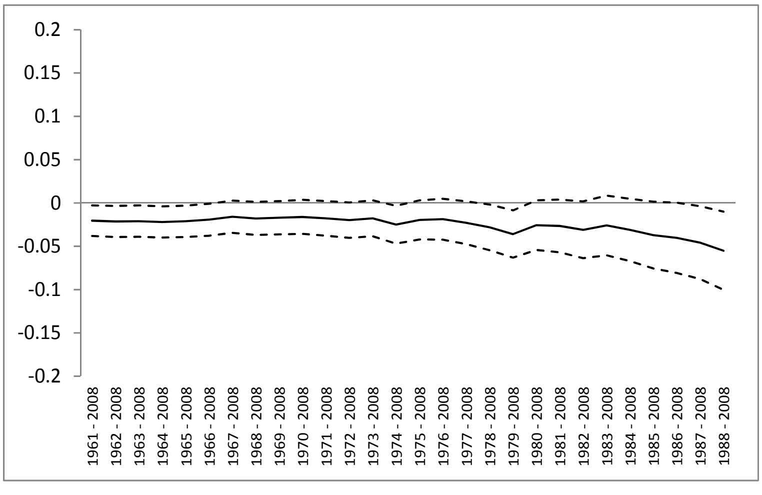


Figure A1b: Price



Note: The x-axis refers to the 'estimation periods' rather than the 'data set periods'.

Figure A2: Model II, Symmetric Price Response with Time Dummies with Fixed-df (coefficients and 95% confidence intervals)

Figure A2a: Income

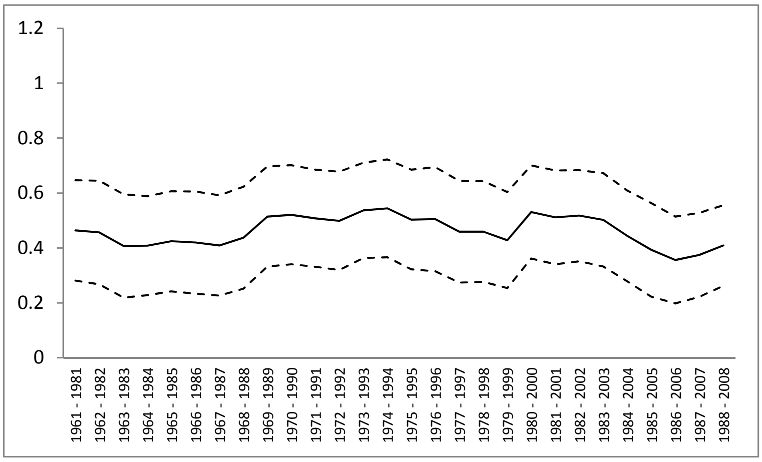
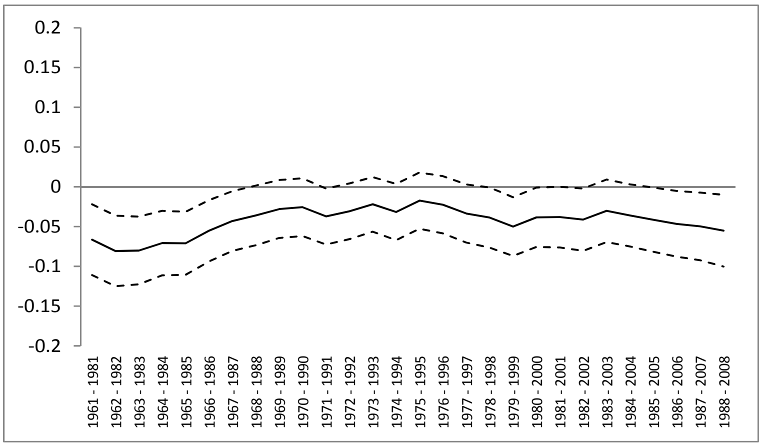


Figure A2b: Price



Note: The x-axis refers to the 'estimation periods' rather than the 'data set periods'.

References

Adeyemi, O. I. and Hunt, L. C., 2007. Modelling OECD Industrial Energy Demand: Asymmetric Price Responses and Energy-saving Technical Change. Energy Economics 29 (4), pp. 693-709.

Adeyemi, O. I., Broadstock, D. C. Chitnis, M. Hunt, L.C. and Judge, G., 2010. Asymmetric Price Responses and the Underlying Energy Demand Trend: Are they Substitutes or Complements? Evidence from Modelling OECD Aggregate Energy Demand. Energy Economics 32(5), pp. 1157 – 1164.

Adofo, Y. O., 2009. Price Decomposition and its Effect on the Stability of Elasticities of Energy Demand for Different Estimation Periods. Unpublished MSc Dissertation, University of Surrey, UK.

Baade, P., 1981. International energy evaluation system: international energy prices: 1955-1980. Information Administration, US Department of Energy Report, SR/STID/81-21, Washington, DC, USA.

BP 2012. Statistical Review of World Energy 2012. Retrieved 10 November 2012 from www.bp.com/statisticalreview/.

Beenstock, M., Willcocks, P., 1981. Energy consumption and economic activity in industrialised countries. Energy Economics 3 (4), pp. 225-232.

Dargay, J. M., 1992. The Irreversible Effects of High Oil Prices: Empirical Evidence for the Demand for Motor Fuels in France, Germany and the UK. in Hawdon, D. (ed.), Energy Demand: Evidence and Expectations, Surrey University Press, Guildford, UK." pp. 165-182

Dargay, J. M., Gately, D., 1995. The Imperfect price-reversibility of non-transport oil demand in the OECD. Energy Economics 17 (1), pp. 59-71.

Dargay, J. M., Gately, D., 1997. The Demand for transportation fuels: imperfect price reversibility?. Transportation Research B 31(1), 71-82.

Dargay, J.M and Gately, D., 2010. World oil demand's shift toward faster growing and less price-responsive products and regions, Energy Policy, 38, pp.6261 – 6277.

Frondel, M., Vance, C., 2013. Re-Identifying the Rebound: What About Asymmetry?, The Energy Journal, 34(2), *forthcoming*.

Gately, D., 1992. Imperfect Price-Reversibility of U.S Gasoline Demand: Asymmetric Responses to Price increases and Decreases. The Energy Journal 13 (4), pp. 179-207.

Gately, D., 1993. The Imperfect price-reversibility of world oil demand. The Energy Journal 14 (4), pp. 163-184.

Gately, D., Huntington, H. G., 2002. The Asymmetric effects of changes in price and income on energy and oil demand. The Energy Journal 23 (1), pp. 19-55.

Griffin, J. M., Schulman, C. T., 2005. Price Asymmetry in energy demand models: A proxy for Energy-saving technical change? The Energy Journal 26 (2), pp. 1-21.

Hunt, L. C., Judge, G., Ninomiya, Y., 2003a. Modelling underlying energy demand trends chapter 9. In: Hunt, L.C. (Ed.), Energy in Competitive Market: Essays in Honour of Colin Robinson. Edward Elgar, UK, pp. 140–174.

Hunt, L. C., Judge, G., Ninomiya, Y., 2003b. Underlying trends and seasonality in UK energy demand: A sectoral analysis. Energy Economics 25(1), pp. 93-118.

Huntington, H., 2006. A note on price asymmetry as induced technical change. The Energy Journal 27 (3), pp. 1-7.

Jones, C. T., 1994. Accounting for Technical Progress in Aggregate Energy Demand. Energy Economics 16 (4), pp. 245-252.

Kouris, G., 1983. Fuel consumption for road transport in the USA. Energy Economics 5, pp. 89–99.

Prosser, R. D., 1985. Demand elasticities in OECD: dynamic aspects. Energy Economics 7(1), pp. 9-12.

Ryan, D. L., Plourde, A., 2002a. Smaller and Smaller? The Price Responsiveness of non-transport Oil Demand. Quarterly Review of Economics and Finance 42, pp. 285-317.

Ryan, D. L., Plourde, A., 2002b. Thanks for the memories: Oil Price Decomposition and Energy Demand Asymmetries. 25th Annual IAEE International Conference, Aberdeen.

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