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Regime-switching Vector Error Correction Model (VECM) analysis of UK meat consumption

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Abstract

The standard Vector Error Correction Model (VECM) approach to investigating the underlying dynamics of economic variables assumes a constant co-integration space. This paper relaxes this assumption by implementing a regime switching VECM that allows for shifts in both the drift and the long-run equilibrium. Applying this more flexible formulation to a study of UK meat consumption, we can clearly identify several shifts in meat consumption. These can be explained by significant shocks in consumer confidence in meat safety, such as BSE. Although it is possible to model these explicitly, since the approach adopted models the regime shift in terms of an unobserved state variable, it can be useful in identifying such shifts, thus allowing them to be modeled in subsequent steps.

Key words: Markov switching, vector autoregression, error correction model

JAE codes: C32, C51, C52

1. Introduction

This study investigates the dynamics of fresh meat consumption in the UK. In particular we pay attention to two analytical aspects of meat demand. Meat consumption time series data in the UK is non-stationary, which justifies the use of standard co-integration methodology. On the other hand, conventional co-integration literature is built around linear models which assume stable relationships. Bearing in mind the dramatic and possibly enduring effects of the BSE crisis and the ample evidence of structural shifts in meat demand, stable relationships are unlikely to persist. Modeling meat demand thus requires one to take account of, and test for, possible structural changes. This paper uses regime-switching methods to model such structural changes.

Data on UK per capita consumption of beef, lamb, pork and poultry meat from the National Food Survey for the period 1974-2000 is used. In the next section we present the econometric issues relating to the adopted methodology and to testing for structural change in co-integrated models in general. Meat consumption dynamics in the UK is then reconsidered in the light of this presentation. The relevant model is estimated and its results interpreted.

2. Econometric issues

Vector autoregressive (VAR) models, introduced by Sims (1980) are widely used in econometric studies. Their popularity is due to the flexibility of the VAR framework and the ease of producing economic models with useful descriptive characteristics, and the availability of statistical tests of economically meaningful hypotheses. It is now increasingly recognised that implications of the linear models, namely linearity (invariance of dynamic multipliers with regard to the history of the system, size and sign of the shocks), time-invariance of parameters and Gaussianity are problematic and better understanding thus requires new econometric tools. In this paper we adopt the regime–switching approach to yield a non-linear model with time-varying coefficients.

While the importance of regime shifts seems to be generally accepted, there is no established theory suggesting a unique approach for specifying econometric models that embody changes in regime. Increasingly however, regime shifts are considered not as singular deterministic events (i.e. structural breaks), but the unobservable regime is assumed to be governed by a stochastic process. Thus regime shifts of the past can be expected to continue to occur in the future in a similar fashion.

When a time series is subject to regime shifts, the parameters of the statistical model will be time-varying. The basic idea of regime-switching models is that the process is time invariant, conditional on a regime variable indicating the regime prevailing at time t. Regime-switching models characterize a non-linear data generating process as being piecewise linear by restricting the process to be linear in each regime, where the regime may be unobservable, and only a discrete number of regimes are feasible. Models within this class differ in their assumptions concerning the stochastic process generating the regime. More specifically we use a Markov-switching vector autoregressive (MS-VAR) model. It assumes the regime S_t is generated by a hidden discrete-state homogeneous and ergodic Markov chain:

$$\Pr(S_t|S_{t-1}; Y_{t-1}; \chi_t) = \Pr(S_t|S_{t-1}; p) \tag{1}$$

defined by the transition probabilities

$$p_{ij} = \Pr(S_{t+1} = j|S_t = i) \tag{2}$$

The conditional process is a VAR(p) with either a shift in the mean corresponding to a once-and-for-all jump in the time series or a shift in the intercept which leads to a smooth adjustment of the time series. This relatively simple formulation can lead to a great variety of flexible models (Krolzig, 1997).

The estimation is based on the state-space form representation of the model, where the so called Hamilton (1989) filter can be applied. This recursive algorithm can be viewed as a discrete version of the Kalman filter usually used in estimating Gaussian state-space models. A major improvement of the smoother has been provided by the backward recursions of Kim (1994). Following Hamilton (1990), the Expectation-Maximization (EM) algorithm (Dempster, Laird and Rubin, 1977) can be used in conjunction with the filter to obtain the maximum likelihood estimates of the model's parameters[1].

The major advantage of this procedure is that it makes use of the discrete support of the state in the MS-VAR model. This allows derivation of the complete conditional distribution of the unobservable state variable instead of deriving the first two moments, as in the conventional Kalman filter (Kalman, 1960, Kalman and Bucy, 1961, Kalman, 1963) for Gaussian linear state-space models, or using the grid-approximation of Kitagawa (1987) for non-linear, non-normal state-space models. Unlike the general non-linear state-space model, this also allows for direct application of Monte Carlo Markov Chain methods for fully Bayesian estimation of such models (see Kim and Nelson, 1998). More detailed discussion of this type of models is beyond the scope of the present study.

Testing for the number of regimes in an MS-VAR model is difficult. The main problem arises from the presence of unidentified nuisance parameters under the null of linearity, which invalidates the conventional testing procedures. (Krolzig, 1997).

The nuisance parameters give the likelihood surface sufficient freedom so that one cannot reject the possibility that the apparently significant parameters could simply be due to sampling variation. The scores associated with parameters of interest under the alternative may be identically zero under the null.

Davies (1977, 1987) derived an upper bound for the significance level of the likelihood ratio test statistic under nuisance parameters. Formal tests of the Markov-switching model against the linear alternative employing a standardized likelihood ratio test designed to deliver (asymptotically) valid inference have been proposed by Hansen (1992, 1996a), Garcia (1998), but are computationally demanding. Alternatively one may use the results of Ang and Bekaert (1998) which indicate that critical values of the $\chi^2(r+n)$ distribution can be used to approximate the LR test, where r is the number of restricted parameters and n is the number of nuisance parameters.

[1] The model innovations are non-Gaussian and thus direct application of the Kalman filter is not feasible.

The simplest alternative used in this paper is to use information criteria for model choice (Akaike, Schwarz and Hannan-Quinn criteria were used) and then check the resulting model congruency by misspecification tests.

The type of MS-VECM we will consider can be represented in the following way using standard co-integration notation (see Krolzig et al., 2002):

$$\Delta y_t = \nu(S_t) + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-i} + \Pi y_{t-p} + u_t \tag{3}$$

where only the constant term is subject to regime change. It is in principle possible to model switching in any component of the model above, but this would entail more complicated estimation algorithms and is still an under-researched area.

Before proceeding we note that the intercept term ν in co-integrated models can be decomposed into two distinct quantities.

To illustrate this let us take expectations of (3) above. This yields:

$$\Gamma(1)E(\Delta y_t) = \nu + \alpha E(\beta' y_t) \tag{4}$$

where we have used the usual decomposition of $\Pi = \alpha\beta'$ into a loading and co-integration matrices and $\Gamma(1) = I - \sum_{i=1}^{p-1} \Gamma_i$.

We can thus represent the intercept ν as follows:

$$\nu = -\alpha E(\beta' y_t) + \Gamma(1)E(\Delta y_t) = -\alpha\delta + \Gamma(1)\mu \tag{5}$$

In (5) above μ denotes the expectation of the first differences of the time series (which exists and is finite if these are I(1) at most) and δ is a constant determining log-run equilibrium and thus is included into the co-integration relation (this is actually the constant term in the co-integration relation).

By rewriting the error correction form of the VAR model we thus identify the underlying growth of the variables (the second term in (5) above), alongside the long-run means of the co-integration relationships (the first term in (5)).

Within the VECM the intercepts can either be restricted to lie in the cointegration space (in which case $\nu = -\alpha\delta$), or not. If the intercepts are not restricted to lie in the cointegration space, they allow the system to have both growth and cointegration means. If, however, the intercepts are restricted, there is no growth in the system, (see Johansen and Juselius, 1990).

Bearing in mind the decomposition of the intercept term in (5) one may identify the following possible regime shifts in the latter: shifts in the long-run equilibrium (i.e. shifts in δ), shifts in the drifts (growth) of the system (i.e. shifts in μ), shifts in both the long-run equilibrium and the drift, or an unrestricted shift (i.e. a shift in ν). In this way the MS-VECM is related to the co-integration literature on structural breaks.

Structural breaks of this type have been widely discussed in the context of univariate autoregressive time series. Perron (1989) suggests three models: Model A, a ’crash model’, with change in intercept but where the slope of the linear trend is unchanged; Model B, a ’changing growth model’, allows a change in the slope of the trend function without any sudden change in the level at the time of the break; and model C, where both intercept and slope are changed at the time of the break. Johansen et al. (2000) present a generalization of model C in a multivariate framework, and allow for testing a hypothesis corresponding to model A.

Saikkonen and Lütkepohl (2000) suggest a two step approach to estimate cointegrated VAR models with structural breaks. In the first step all the coefficients for the deterministic variables are estimated. In the second step a normal cointegration analysis is conducted, but the deterministic components are removed from each time series. The estimation in the second step is therefore done without any deterministic variables included. One problem with this estimation method is that not all restrictions among the coefficients for the deterministic variables can be taken into account in the first step. In the same way as for the estimation procedure in Johansen et al. (2000) this involves a reduction in the degrees of freedom when the coefficients for the deterministic variables are estimated. Hungnes (2002) proposes testing procedures based on the switching algorithm of Boswijk (1995).

The main advantage of the MS-VECM approach is that it nests the structural breaks models in that they are particular cases of the MS-VECM model when one of the states is absorbing. Additionally the alternatives for switching allow for a great deal of flexibility. Note that while switches in the drift (i.e. μ) are expressed in abrupt changes in the data, shifts in the long-run equilibrium (i.e. δ) are transmitted smoothly through the system in a similar way as in smooth transition models.

When considering a model incorporating a structural change it might be useful to review the concept of co-breaking introduced by Hendry (1996) and Hendry and Mizon (1998). If deterministic breaks in a system of equations can be removed by taking linear combinations of the system variables, the variables are said to co-break. Co-breaking analyses are not ubiquitous. The reason is that one needs at least as many breaks as variables in the system. If not, there will always exist at least one linear combination of the variables where the deterministic breaks can be removed. Hendry and Mizon (1998) label such situations as 'spurious co-breaking'. It can be shown that in an MS-VECM with regime dependent intercepts only, the co-integrating vectors yield co-breaking relationships, which ensures the stationarity of the model, even if the regime shifts are not themselves co-breaking.

With regard to meat consumption, the most interesting type of structural change would be an abrupt change in the drift of the system. This is also the simplest type of MS-VECM model, since it preserves the co-integration space. Moreover the experience of structural changes such as those following the BSE consumer food safety confidence crisis suggests such type of shifts. Other changes such as the entry to the EU, preference and health related diet changes however assume a gradual process of adjustment that is better represented by shifts in the long run equilibrium state. An advantage of such an approach is that it allows us to use the established results from the theory of linear co-integrated processes and estimate a conventional VECM at the first step, which then can be used with no alteration in estimating the final MS-VECM[2].

3. How to model the UK meat consumption

One of the largest UK food markets is that of meat. Meat is an important source of human nutrition. However, over the past two decades, there have been many opinions on the value of meat in the diet leading to a continuous debate over the advantages

[2] The same type of two step procedure can be used for all types of shift discussed here. It would rely on an approximation of the infinite order VAR (the MS-VECM has an observationally equivalent VARMA representation) by a finite order liner VAR which is estimated at the first step.

and disadvantages of eating meat. The traditional British meal however still tends to include meat as its main part. Since the 1980s however, there has been a shift away from consumption of red meat towards white meat. This has created trends in meat consumption that present analytical interest. In the econometric framework developed in the previous section, this requires that our model should not be restricted in the sense of restricting the drifts in the intercept term to be zero.

In a Monte Carlo simulation Doornik (1998) shows that if the system is misspecified by not including a trend, we may not identify all the cointegrating vectors. This is because the deterministic trends will be represented by a stochastic trend. To erroneously include a deterministic trend however has a very low cost.

A series of food scares, most prominently BSE, have also had a marked affect on the British meat industry. Influenced by these disease scares and releases such as the '1984 COMA Report', which outlined recommendations on reducing the level of fat in human diets, the British public has become more aware of what they are eating, and have adjusted their consumption trends. Changes in the structure of society and family, have also influenced the meat industry. There has been a shift away from the traditional British roasts, towards other types of food such as ready prepared meals, and foreign cuisine. In general all these factors have created a tendency to move away from red meats towards white meats.

With regard to the MS-VECM, this means that such socio-economic forces would induce changes in the drift of the system. It is possible in addition to also have effect on the co-integrating space (i.e. to shift the stochastic trends as well).

In selecting data for this study we have also taken into consideration that the trends and tendencies described above only appeared in the 1980s. The National Food Survey holds data since 1949. Due to expected difference even in the stochastic trends present in meat consumption in the post-war period and the most recent years there exists a danger of misspecification, in the sense that a more appropriate model may involve regime switching for the cointegrating vectors themselves. For these reasons we reduce the sample and start from 1974, the year following the entry of the UK into the EU.

4. Estimation Results

Prior to analysis we take natural logarithms of all data.

4.1 Stationarity testing

Testing economic data for stationarity is nowadays a widespread exercise. In the realms of co-integration literature this is often equivalent to testing for a unit root. There are numerous unit root tests available in the literature

Unit root tests consist of univariate and covariate tests. Testing for unit roots in a univariate time series ignores relevant information contained in other time series. Hansen (1995) and Elliott and Jansson (2003) derive covariate unit root tests with substantial power gains over their conventional unit root counterparts by exploiting the information in related time series. These tests increase power by modeling correlated stationary economic variables with the dependent variable. The use of stationary covariates results in a new error variance that is smaller than the error variance of a univariate regression. This results in smaller confidence intervals and more powerful test statistics than those of the conventional unit root tests. In the case of meat consumption however it is difficult to find appropriate stationary covariates.

Due to the unclear power of the unit root tests, it is advisable to use several of these to obtain robust results. Here we employ the following univariate unit root tests: the Augmented Dickey Fuller (ADF) test of Dickey and Fuller (1979), the generalized least squares ADF and the Point Optimal test of Elliott, Rothenburg, and Stock (1996), and the Phillips and Perron (1988) test.

The second family of univariate tests, namely stationarity tests, reverses the null and alternative hypotheses of the unit root tests. The stationarity test examines the null hypothesis of level or trend stationarity, I(0), against the alternative of difference stationarity, I(1). Examples of such tests include those of Kwiatkowski, Phillips, Schmidt, and Shin (1992) (KPSS), Saikkonen and Luukkonen (1993), and Leybourne and McCabe (1994). In this study we employ the most widely used of these tests the KPSS one. It is advantageous to combine the test with the null of stationarity and of unit root to make the results robust.

When however one tries to model a system of economic variables, the potential correlation amongst these may decrease the power of a univariate unit root test. This is the basic idea behind the panel unit root tests which include the other time series from a panel in order to increase the power of the unit root test. The same logic can be applied to any group of time series, particularly if these are to be modeled simultaneously. Therefore we use some of the panel unit root tests, namely those of Levin, Lin and Chu (2002), Breitung (2002), Im, Pesaran and Shin (2003), and Fisher-type tests using ADF and PP tests (Maddala and Wu (1999) and Choi (2001)). Additionaly we employ the stationarity panel test due to Hadri (1999). Although these tests are commonly termed “panel unit root” tests, they are simply multiple-series unit root tests that have been applied to panel data structures (where the presence of cross-sections generates “multiple series” out of a single series). All the above panel unit roots are very different in their assumptions, but discussing their differences and similarities is not the subject to this study.

The results from the univariate unit root tests are presented in table 1. In general due to the very small sample size the ERS test results do not seem reliable (the critical values are for a sample of size 50). Otherwise broadly speaking most tests provide evidence for unit root in the levels, but no unit roots in the first differences. In the cases of poultry and to some extent lamb, including a linear trend in the test equation tends to lead to the conclusion of no unit root. The stationarity test (KPSS) seems to confirm the trend stationarity of lamb consumption, but rejects it for poultry. Given that the confidence level of rejection of the null of a unit root are much higher in the poultry case, this suggests the possibility for fractional order of integration.

Table 2 presents the results from the panel unit roots for all 4 series, using different criteria for lag choice. Whilst the null of no common unit root is strongly rejected in all cases, these tests reject the null of unit roots in the case of the presence of a linear trend.

If however we carry out the same panel unit root tests on a reduced panel that excludes poultry consumption (see table 3), the evidence for unit roots increases. If we further exclude lamb, the confidence limit of these tests increases even further (results available from the authors). Another interesting result from the panel unit root tests is that even in the larger panel, the tests that tend to reject the null of unit root in the case of a deterministic trend assume individual unit root processes. The tests that assume common unit roots fail to reject the null and accordingly the Hadri (2000) test which has stationarity as it null against an alternative of common unit roots is highly significant. We thus find strong evidence for the presence of unit roots in beef and pork consumption, whilst for lamb and poultry consumption we are unable to definitely reject trend stationarity. This finding means that it is highly likely that these series share common unit root processes and thus require co-integration analysis.

4.2 VECM

Bearing in mind the mixed results from the unit root tests, we now proceed to testing for co-integration and estimating a VECM. An important question on the structure of the VECM is whether poultry and lamb consumption need to be included, given the relatively weak evidence for unit roots in these series. The Granger causality tests on the four series however indicate that lamb consumption is Granger caused by beef consumption, which warrants the inclusion of lamb consumption in the VAR model. The question with poultry consumption is more complicated. The Granger causality tests show that it is exogenous with regard to the other variables. Nevertheless since we are also unable to accept the stationarity of poultry consumption, we include it in the system.

More detailed results are presented in appendix 1. Note the inclusion of a time trend in the co-integrating relationship. This is warranted in order to avoid the spurious detection of more co-integrating vectors (see Doornik, 1998).

The main point of interest in this step is the identification of the long-run co-integrating relationship. We are able to identify a single co-integrating vector. We use the latter to construct the error-correction term for the MS-VECM in the next step.

4.3 MS-VECM of meat consumption

This is the main focus of the present study. It involves generalizing the estimated VECM of UK meat consumption to a MS-VECM. There are two issues to consider in this process. The first is whether the Markov switching mechanism is necessary. We note that this involves testing a non-linear (MS-VECM) against a linear (VECM) alternative. A more general approach would be to test the residuals from the VECM estimation for non-linearity. The problem with such an approach is that it can only detect non-linearity, but would not be able to determine what is the appropriate alternative model. Moreover one may sometimes interpret the results from such tests as an indication of general model misspecification. Therefore we choose to implement an LR test for an ordinary VECM against the MS-VECM. The problem with such a test is that there are nuisance parameters which are present in the second case. Therefore the LR needs to be adjusted or obtain an upper significance bound according to the suggestions of Davies (1977,1987). In addition we also present the Chi square approximation due to Ang and Bekaert (1998).

The other issue is the choice of number of regimes. We use the information criteria to do so. The main information criterion used is the Bayesian Schwarz information criterion, although the other two information criteria (Akaike and Hannan-Quinn) yield the same model.

The estimation results are presented in Appendix 2. The LR linearity test strongly rejects the linear VECM in favour of the MS-VECM. In this case we apply an unrestricted shift to the intercept. If only the drift is shifted we are not able to reject the null of linearity (Results available from the authors upon request) although the general structure of the resulting MS-VECM is similar to the one presented here in terms of estimated coefficients and the regime classification coincides with ours. This is an indication that there are also shifts occurring to the long-term equilibrium of the system. Although it is advisable to represent these separately, due to the small sample we ran into numerical problems in estimating a more general model.

The residuals from the estimated MS-VECM can be tested for additional non-linearity. This involves bootstrapping the available non-linearity test to account for the small sample bias. To simplify the presentation we omit these test results, but they are available upon request.

Additionally in appendix 3 we present generalized regime dependent impulse response functions (IRFs) from the MS-VECM, estimated alongside the suggestions of Ehrmann *et al*. (2003)[3] using 500 bootstrap replications. Since we only switch the intercept, these are similar for both regimes. Therefore we only present the impulse response functions for regime 1 (which can be broadly defined as the 'normal' regime). An important consideration in constructing these is to select the length of the response which should not extend beyond the average length of the regime. Based on

[3] We are grateful to Michael Ehrmann for allowing us to use their code. We only made some slight modifications to it in order to adjust it for our purpose.

the estimation results we choose an 8 periods (years) response projection. One may see from the IRFs the uncharacteristic reaction in the last period. This is not be surprising since the two longest periods in regime 1 in the data are of length 8 and 6. A careful examination of these impulse response functions suggests that a more detailed study of the possibility of co-breaking relationships (other than the one implied by co-integration) may be useful to further identify the dynamics of meat consumption. One should note the clear similarities in the IRFs for pork and poultry. In addition to suggesting the possible co-breaking relationship between these two variables, this warrants the inclusion of poultry consumption in the estimated system.

Conclusions

This paper analyses UK meat consumption using a MS-VECM. We find strong evidence against the conventional linear co-integration model. Furthermore, although the model allows for an absorbing state, in which case we would have the typical structural break model, this does not appear to be the case. Meat consumption instead, is governed by a latent process of continuous change. We find evidence for shifts in both the drift and the long-term equilibrium of the consumption system. We present results from numerous unit root tests with a twofold purpose. First these test are known to often have low power and combining them can in general be advantageous. The results for the unit root testing procedures are mixed. It should however be noted that the notion of non-stationarity is much wider than the simplistic unit root paradigm. Non-stationarity and non-linearity can be easily confused, and in this case we clearly have a non-linear process. Additionally the unit root tests have low power to alternatives such as the stochastic unit root processes (Leybourne et al, 1996) and Granger and Swanson, 1997), fractionally integrated processes or indeed regime–switching (see e.g. Nelson *et al*., 2001)[4]. It is thus desirable to perform more model-based type unit root testing.

A question that might be asked is what are the driving forces of the underlying regimes. In Gordon and St-Armour (2000) the power coefficient in the constant relative risk aversion (CRRA) utility function is assumed to obey a two-state Markov chain, allowing agents' sentiments to switch from one state to another in a manner

[4] These issues are intrinsically related. Stochastic unit root processes are fractionally integrated and it is difficult even asymptotically to distinguish long memory and regime switching.

reminiscent of Keynes' 'animal spirits'. One can readily generalize such a micro model in allowing social factors, as for example the press, to influence an unobservable variable- the 'public opinion' which in its turn can determine the prevailing consumption regime. If one knows these social factors an explained switching model may be more appropriate, but the approach employed here is much more general.

An important result from this study is that the constancy of the linear co-integration space for meat consumption in the UK cannot be maintained in the sense that the identified long-run equilibrium is moving in time and within the regime switching process. An alternative avenue of research would be to test for a non-linear co-integration. Note that a more often used label for the abbreviation VECM is 'Vector Equilibrium Correction Model'. We resisted using the latter because the MS-VECM representation not only leads to multiple equilibria (according to the different regimes), but also assumes a constantly changing long-run equilibrium. From an estimation point of view the long-term equilibrium would be defined by the relative regime probabilities. It should be clear that since the exact timing of future regime changes cannot be predicted, then the log-run equilibrium can be subject to a kind of path dependency. This seems to contradict the conventional view of equilibrium, but presents a more realistic view of economic processes.

Some preliminary results from employing the more robust, though extremely computationally demanding approach to testing for regime switching based on the tests suggested by Hansen (1992, 1996a) and Garcia (1998), which are available from the authors upon request, tend to suggest an alternative model with asynchronous regime switching, as opposed to the simultaneous one employed here.

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Table1 Univariate root tests results

Variable	Test	level	1st difference	Details
BF	ADF	-0.522422	*** -5.860520	SIC;Cst
BF	ADF	-3.113209	*** -5.561496	SIC;Cst,Tr
BF	DF-GLS	-0.380620	-1.101391	SIC;Cst
BF	DF-GLS	-2.630299	*** -5.334123	SIC;Cst,Tr
BF	PP	-0.460248	*** -5.828962	NW, B;Cst
BF	PP	-3.123622	*** -5.543996	NW, B;Cst,Tr
BF	ERS	31.23937	5.152819	SIC, SOLS;Cst
BF	ERS	17.06255	11.17397	SIC, SOLS;Cst,Tr
BF	KPSS	** 0.714030	0.150600	NW, B;Cst
BF	KPSS	* 0.121031	* 0.132829	NW, B;Cst,Tr
LM	ADF	-0.529912	*** -5.953537	SIC;Cst
LM	ADF	* -3.285312	*** 5.835131	SIC;Cst,Tr
LM	DF-GLS	-0.351129	*** -5.724574	SIC;Cst
LM	DF-GLS	* -3.124824	*** -6.012916	SIC;Cst,Tr
LM	PP	-0.363025	*** -6.018475	NW, B;Cst
LM	PP	* -3.285312	*** -5.893026	NW, B;Cst,Tr
LM	ERS	25.43133	** 2.304275	SIC, SOLS;Cst
LM	ERS	10.74107	7.353644	SIC, SOLS;Cst,Tr
LM	KPSS	** 0.734722	0.104627	NW, B;Cst
LM	KPSS	0.086298	0.075991	NW, B;Cst,Tr
PK	ADF	-0.640332	*** -5.871772	SIC;Cst
PK	ADF	-2.034204	*** -6.364641	SIC;Cst,Tr
PK	DF-GLS	-0.994483	*** -4.792133	SIC;Cst
PK	DF-GLS	-2.010803	*** -5.795921	SIC;Cst,Tr
PK	PP	0.844906	*** -5.870476	NW, B;Cst
PK	PP	-1.825416	*** -6.459092	NW, B;Cst,Tr
PK	ERS	10.7627	* 3.589194	SIC, SOLS;Cst
PK	ERS	16.87547	10.31715	SIC, SOLS;Cst,Tr
PK	KPSS	** 0.503207	0.177237	NW, B;Cst
PK	KPSS	** 0.148918	0.112140	NW, B;Cst,Tr
PL	ADF	-2.356564	*** -4.955080	SIC;Cst
PL	ADF	*** -3.996804	*** -5.204597	SIC;Cst,Tr
PL	DF-GLS	-0.906349	*** -5.179466	SIC;Cst
PL	DF-GLS	** -3.378108	*** -6.692671	SIC;Cst,Tr
PL	PP	* -2.861776	*** -7.81352	NW, B;Cst
PL	PP	** -4.202943	*** -13.46409	NW, B;Cst,Tr
PL	ERS	55.27378	** 2.119375	SIC, SOLS;Cst
PL	ERS	16.09524	** 4.662476	SIC, SOLS;Cst,Tr
PL	KPSS	*** 0.756815	* 0.377711	NW, B;Cst
PL	KPSS	*** 0.172347	**** 0.500000	NW, B;Cst,Tr

Notes:

SIC	Schwartz Information criterion
Cst	constant
Tr	linear trend
NW	Newley-West bandwith choice
B	Balrlet kernel
SOLS	Spectral OLS
***	Significant at 1% level
**	Significant at 5% level
*	Significant at 10% level

Table 2 Panel Unit root tests results

	AIC		AIC	TR	SIC		SIC,	TR	HQ		HQ	TR
Method	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.
Null: Unit root (assumes common unit root process)												
Levin, Lin & Chu t*	-0.3102	0.3782	-1.9478	0.0257	-0.61747	0.2685	-2.28072	0.0113	-0.44785	0.3271	-1.9478	0.0257
Breitung t-stat	0.75317	0.7743	1.05137	0.8535	0.31523	0.6237	0.99200	0.8394	0.58954	0.7223	1.05137	0.8535
Null: Unit root (assumes individual unit root process)												
Im, Pesaran and Shin W-stat	1.10906	0.8663	-2.3814	0.0086	0.98298	0.8372	-2.2322	0.0128	1.09087	0.8623	-2.3814	0.0086
ADF - Fisher Chi-square	3.63543	0.8884	18.7496	0.0163	4.70861	0.7882	17.7912	0.0228	4.00270	0.8569	18.7496	0.0163
PP - Fisher Chi-square	6.43365	0.5988	18.3655	0.0186	6.43365	0.5988	18.3655	0.0186	6.43365	0.5988	18.3655	0.0186
Null: No unit root (assumes common unit root process)												
Hadri Z-stat	7.20996	0.0000	3.03267	0.0012	7.20996	0.0000	3.03267	0.0012	7.20996	0.0000	3.03267	0.0012

	MAIC		MAIC	TR	MSIC		MSIC	TR	MHQ		MHQ	TR
Method	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.	Statistic	Prob.
Null: Unit root (assumes common unit root process)												
Levin, Lin & Chu t*	-0.10376	0.4587	-2.28072	0.0113	-0.44785	0.3271	-2.28072	0.0113	-0.4478	0.3271	-2.2807	0.0113
Breitung t-stat	-0.02317	0.4908	0.99200	0.8394	0.58954	0.7223	0.99200	0.8394	0.58954	0.7223	0.99200	0.8394
Null: Unit root (assumes individual unit root process)												
Im, Pesaran and Shin W-stat	1.15344	0.8756	-2.2322	0.0128	1.09087	0.8623	-2.2322	0.0128	1.09087	0.8623	-2.2322	0.0128
ADF - Fisher Chi-square	3.85718	0.8698	17.7912	0.0228	4.00270	0.8569	17.7912	0.0228	4.00270	0.8569	17.7912	0.0228
PP - Fisher Chi-square	6.43365	0.5988	18.3655	0.0186	6.43365	0.5988	18.3655	0.0186	6.43365	0.5988	18.3655	0.0186
Null: No unit root (assumes common unit root process)												
Hadri Z-stat	7.20996	0.0000	3.03267	0.0012	7.20996	0.0000	3.03267	0.0012	7.20996	0.0000	3.03267	0.0012

AIC -Akaike, SIC -Schwatz, HQ – Hannan-Quinn; M - modified

Table 3 Reduced panel (BF, PK and LM) Unit root tests

Method	AIC Statistic	TR Prob.	SIC Statistic	TR Prob.	HQ Statistic	TR Prob.	MAIC Statistic	TR Prob.	MSIC Statistic	TR Prob.	MHQ Statistic	TR Prob.
Null: Unit root (assumes common unit root process)												
Levin, Lin & Chu t*	-0.35729	0.3604	-0.81128	0.2086	-0.35729	0.3604	-0.81128	0.2086	-0.81128	0.2086	-0.81128	0.2086
Breitung t-stat	1.34213	0.9102	1.24846	0.8941	1.34213	0.9102	1.24846	0.8941	1.24846	0.8941	1.24846	0.8941
Null: Unit root (assumes individual unit root process)												
Im, Pesaran and Shin W-stat	-1.52092	0.0641	-1.32303	0.0929	-1.52092	0.0641	-1.32303	0.0929	-1.32303	0.0929	-1.32303	0.0929
ADF - Fisher Chi-square	11.1004	0.0853	10.1421	0.1188	11.1004	0.0853	10.1421	0.1188	10.1421	0.1188	10.1421	0.1188
PP - Fisher Chi-square	9.82785	0.1321	9.82785	0.1321	9.82785	0.1321	9.82785	0.1321	9.82785	0.1321	9.82785	0.1321
Null: No unit root (assumes common unit root process)												
Hadri Z-stat	2.52110	0.0058	2.52110	0.0058	2.52110	0.0058	2.52110	0.0058	2.52110	0.0058	2.52110	0.0058

Pairwise Granger Causality Tests

Null Hypothesis:	Obs	F-Statistic	Probability
LNLM does not Granger Cause LNBF	24	2.08912	0.13958
LNBF does not Granger Cause LNLM		2.77301	0.07319
LNPK does not Granger Cause LNBF	24	0.36523	0.77897
LNBF does not Granger Cause LNPK		4.14776	0.02236
LNPL does not Granger Cause LNBF	24	1.84174	0.17788
LNBF does not Granger Cause LNPL		0.76298	0.53030
LNPK does not Granger Cause LNLM	24	0.05989	0.98015
LNLM does not Granger Cause LNPK		3.70861	0.03215
LNPL does not Granger Cause LNLM	24	0.74866	0.53799
LNLM does not Granger Cause LNPL		1.45268	0.26267
LNPL does not Granger Cause LNPK	24	8.49499	0.00114
LNPK does not Granger Cause LNPL		0.75494	0.53460

Appendix1

VECM estimation

Cointegration Rank Test

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	5 Percent Critical Value	1 Percent Critical Value
None **	0.747867	70.05084	62.99	70.05
At most 1	0.552190	36.98366	42.44	48.45
At most 2	0.357296	17.70237	25.32	30.45
At most 3	0.255862	7.092683	12.25	16.26

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	5 Percent Critical Value	1 Percent Critical Value
None *	0.747867	33.06717	31.46	36.65
At most 1	0.552190	19.28129	25.54	30.34
At most 2	0.357296	10.60969	18.96	23.65
At most 3	0.255862	7.092683	12.25	16.26

*(**) denotes rejection of the hypothesis at the 5%(1%) level
Max-eigenvalue test indicates 1 cointegrating equation(s) at the 5% level

Unrestricted Cointegrating Coefficients (normalized by b'*S11*b=I):

LNBF	LNPK	LNPL	LNLM	TREND
4.632024	14.46651	-67.80305	-7.932211	1.236427
0.220762	-5.211727	-16.72543	18.36359	0.907345
-5.361773	-14.31232	26.31200	-1.413653	-1.004059
19.28423	-7.967016	-3.804871	1.660707	0.629353

Unrestricted Adjustment Coefficients (alpha):

D(LNBF)	0.007704	0.013163	0.005283	-0.029430
D(LNPK)	0.005296	0.004931	0.035186	0.001117
D(LNPL)	0.033087	0.001327	-0.001854	0.009118
D(LNLM)	-0.003538	-0.064037	0.020969	0.007116

Normalized cointegrating coefficients (std.err. in parentheses)

LNBF	LNPK	LNPL	LNLM	TREND
1.000000	3.123151	-14.63789	-1.712472	0.266930
	(0.78351)	(2.35541)	(0.67660)	(0.05248)

Adjustment coefficients (std.err. in parentheses)

D(LNBF)	0.035686
	(0.07628)
D(LNPK)	0.024531
	(0.07348)
D(LNPL)	0.153258
	(0.03291)
D(LNLM)	-0.016390
	(0.11652)

VECM estimation results

Error Correction:	D(LNBF)	D(LNPK)	D(LNPL)	D(LNLM)
CointEq1	0.062073	-0.094351	-0.186571	0.056595
	(0.08770)	(0.10209)	(0.03532)	(0.10266)
	[0.70780]	[-0.92421]	[-5.28298]	[0.55131]
D(LNBF(-1))	-0.103960	-0.076126	0.274388	-0.017883
	(0.31247)	(0.36374)	(0.12583)	(0.36576)
	[-0.33270]	[-0.20928]	[2.18063]	[-0.04889]
D(LNBF(-2))	-0.297045	0.113367	0.537288	0.577702
	(0.30022)	(0.34948)	(0.12090)	(0.35142)
	[-0.98943]	[0.32439]	[4.44422]	[1.64390]
D(LNPK(-1))	-0.141234	-0.351500	0.105228	0.164971
	(0.25833)	(0.30072)	(0.10403)	(0.30239)
	[-0.54672]	[-1.16886]	[1.01153]	[0.54556]
D(LNPK(-2))	-0.477624	0.019357	0.418797	0.300841
	(0.25111)	(0.29231)	(0.10112)	(0.29394)
	[-1.90206]	[0.06622]	[4.14158]	[1.02349]
D(LNPL(-1))	-0.720055	1.364414	1.044118	0.260862
	(0.73819)	(0.85932)	(0.29727)	(0.86409)
	[-0.97543]	[1.58778]	[3.51241]	[0.30189]
D(LNPL(-2))	-1.009482	0.883064	1.192473	0.722047
	(0.69620)	(0.81044)	(0.28036)	(0.81494)
	[-1.44998]	[1.08961]	[4.25342]	[0.88601]
D(LNLM(-1))	0.175873	-0.198117	-0.236009	-0.667956
	(0.22911)	(0.26671)	(0.09226)	(0.26819)
	[0.76763]	[-0.74283]	[-2.55803]	[-2.49063]
D(LNLM(-2))	0.155130	-0.036460	-0.013346	-0.213624
	(0.17099)	(0.19905)	(0.06886)	(0.20015)
	[0.90724]	[-0.18317]	[-0.19382]	[-1.06730]
C	-0.770378	0.581413	1.426179	0.493853
	(0.63561)	(0.73990)	(0.25596)	(0.74401)
	[-1.21203]	[0.78580]	[5.57199]	[0.66377]
PLNBF	-0.128070	-0.373975	-0.255013	-0.784648
	(0.32817)	(0.38202)	(0.13215)	(0.38415)
	[-0.39025]	[-0.97893]	[-1.92967]	[-2.04258]
PLNPK	-1.160335	-0.027098	0.882727	1.657115
	(0.42581)	(0.49568)	(0.17147)	(0.49843)
	[-2.72502]	[-0.05467]	[5.14799]	[3.32466]
PLNPL	0.089328	0.830702	0.372232	0.905056
	(0.50789)	(0.59122)	(0.20452)	(0.59451)
	[0.17588]	[1.40505]	[1.82000]	[1.52236]
PLNLM	0.576641	-0.206594	-0.008589	-1.834443
	(0.40529)	(0.47179)	(0.16321)	(0.47441)
	[1.42280]	[-0.43790]	[-0.05262]	[-3.86680]
R-squared	0.656009	0.635802	0.893908	0.766748
Adj. R-squared	0.208821	0.162345	0.755987	0.463520

S.E. equation	0.064908	0.075558	0.026138	0.075978
Log likelihood	42.08610	38.43961	63.91602	38.30666
Akaike AIC	-2.340509	-2.036634	-4.159668	-2.025555
Schwarz SC	-1.653311	-1.349436	-3.472470	-1.338357
Mean dependent	-0.023317	-0.007289	0.016566	-0.032507
S.D. dependent	0.072972	0.082556	0.052913	0.103731

Determinant Residual Covariance	5.55E-11
Log Likelihood	189.1768
Log Likelihood (d.f. adjusted)	147.1543
Akaike Information Criteria	-7.179527
Schwarz Criteria	-4.185307

Appendix 2
MS-VAR estimation results

```
EQ( 1) MSI(2)-VARX(2) model of (BF,LM,PK,PL),
no. obs. per eq. :      22
in the system :         88
no. parameters   :      56
linear system :         50
no. restrictions :       4
no. nuisance p.  :       2

log-likelihood   :147.2699
linear system :   137.4848

AIC criterion       -8.2973
linear system :     -7.9532
HQ  criterion       -7.6430
linear system       -7.3690
SC  criterion       -5.5201
linear system       -5.4735

LR linearity test:    19.5702
Chi(4) = [0.0006] **
Chi(6) = [0.0033] **
DAVIES = [0.0114] *
```

Chi(4) and Chi(6) are the Ang and Bekaert (1998) approximation. Davies is the Davies(1987) upper significance bound

---------- transition matrix ----------------------

	Regime 1	Regime 2
Regime 1	0.7889	0.2111
Regime 2	0.4586	0.5414

	nObs	Prob.	Duration
Regime 1	15.0	0.6848	4.74
Regime 2	7.0	0.3152	2.18

---------- coefficients ---------------------------

	BF	LM	PK	PL
Const(Reg.1)	-0.028216	-0.071107	-0.070770	0.034978
Const(Reg.2)	0.025462	0.044924	0.058726	0.027219
BF_1	-0.102750	0.072132	-0.109295	0.052031
BF_2	0.343720	0.694391	0.447013	-0.163419
LM_1	-0.100473	-0.310709	-0.174450	-0.004741
LM_2	0.253495	-0.027892	0.049843	0.096577
PK_1	0.091380	-0.400893	-0.338273	0.230263
PK_2	-0.311461	-0.126610	-0.081292	0.108650

PL_1	-0.007793	0.094072	1.066368	-1.197793
PL_2	-0.282892	0.338389	-0.081754	0.547490
COIN_1	-0.002227	-0.073227	-0.083856	0.159827
SE	0.060427	0.085568	0.035470	0.026903

---------- contemporaneous correlation -------------

	BF	LM	PK	PL
BF	1.0000	-0.6214	-0.2332	-0.5755
LM	-0.6214	1.0000	-0.1513	0.0448
PK	-0.2332	-0.1513	1.0000	0.1184
PL	-0.5755	0.0448	0.1184	1.0000

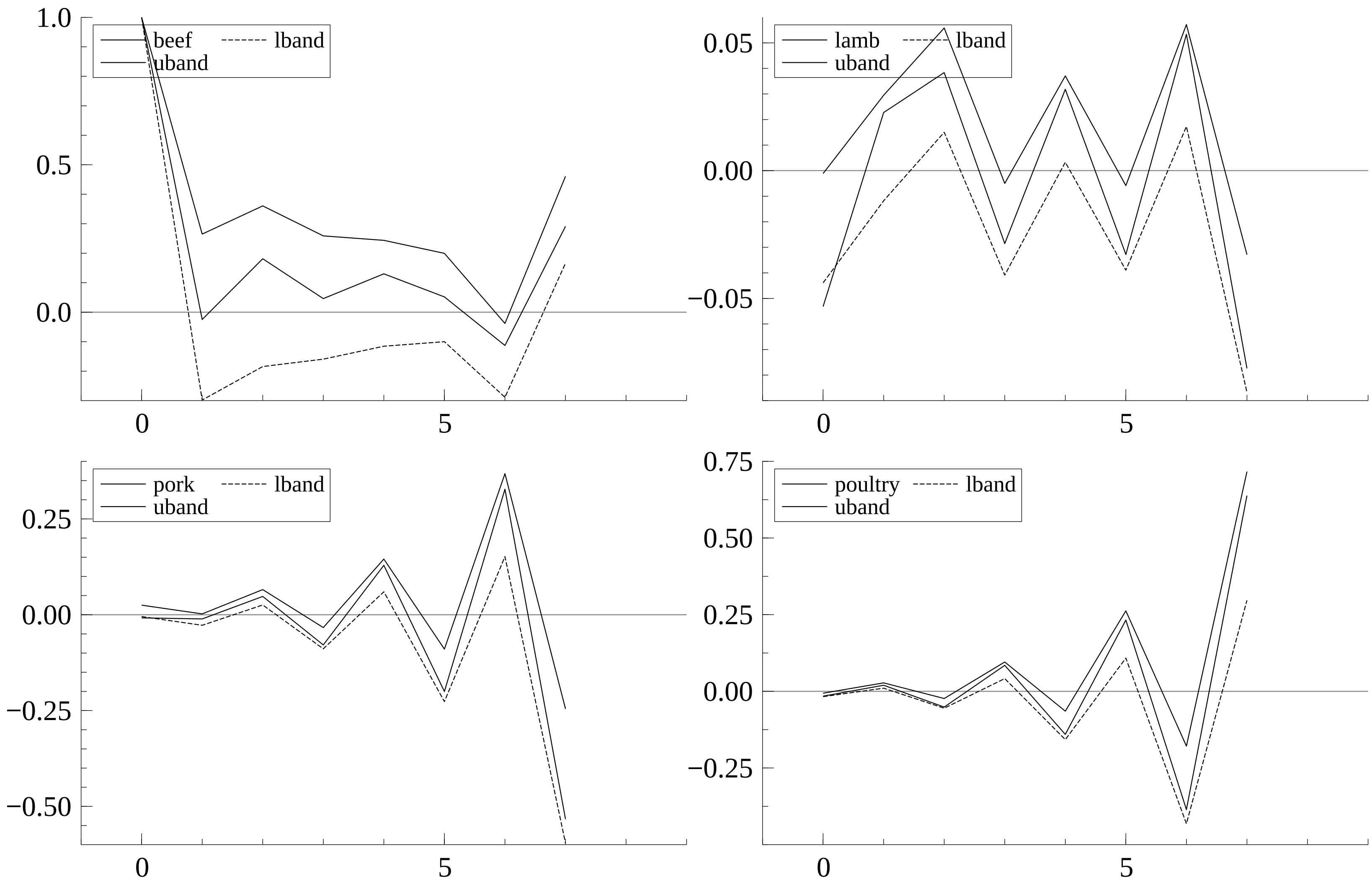
---------- regime classification -------------------

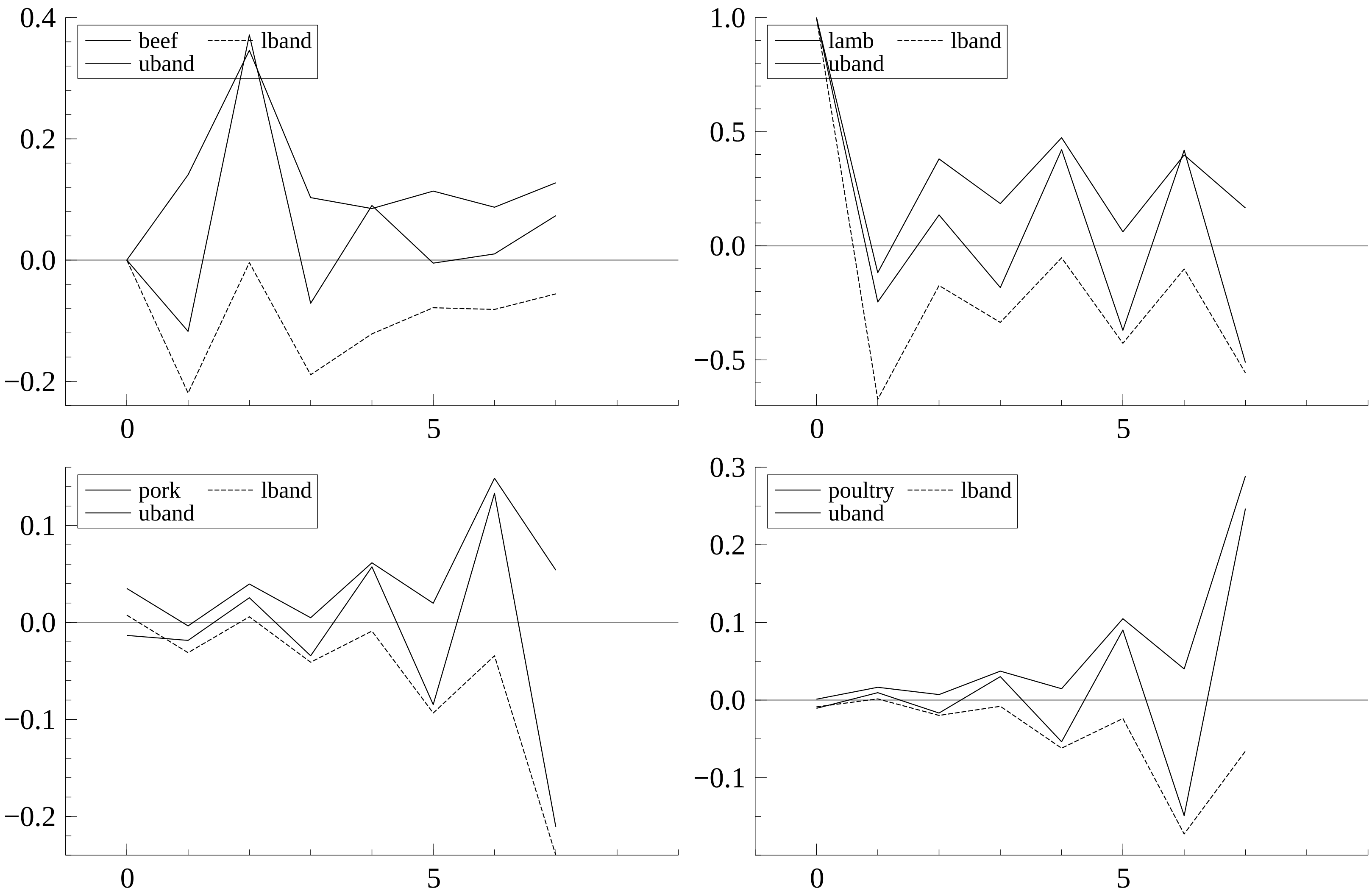
Regime 1
1981 - 1985
1987 - 1995
1999 - 1999

Regime 2
1979 - 1980
1986 - 1986
1996 - 1998
2000 - 2000

Appendix 3
Regime dependent impulse response functions

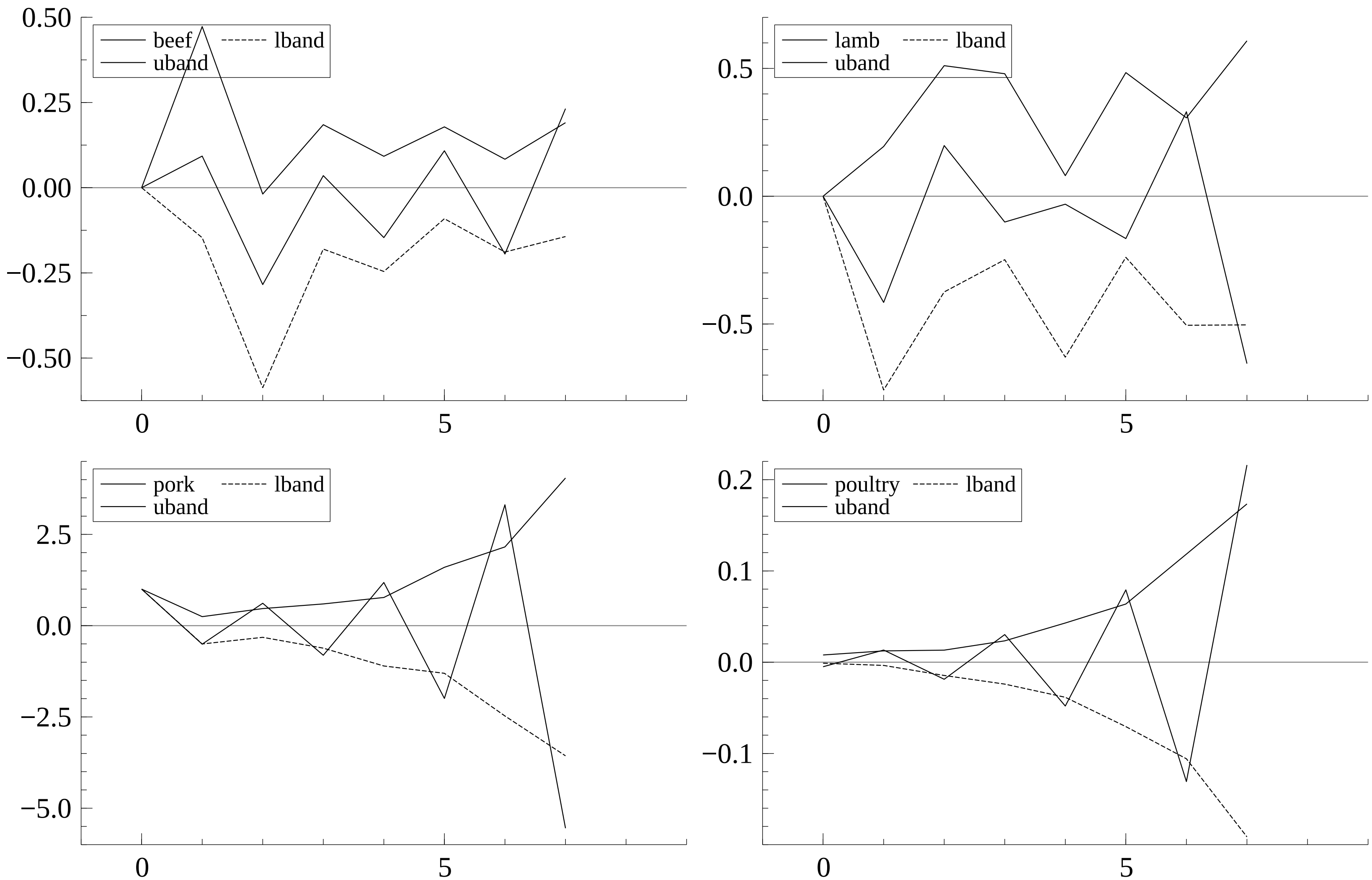
Response of meat consumption to a shock to beef consumption

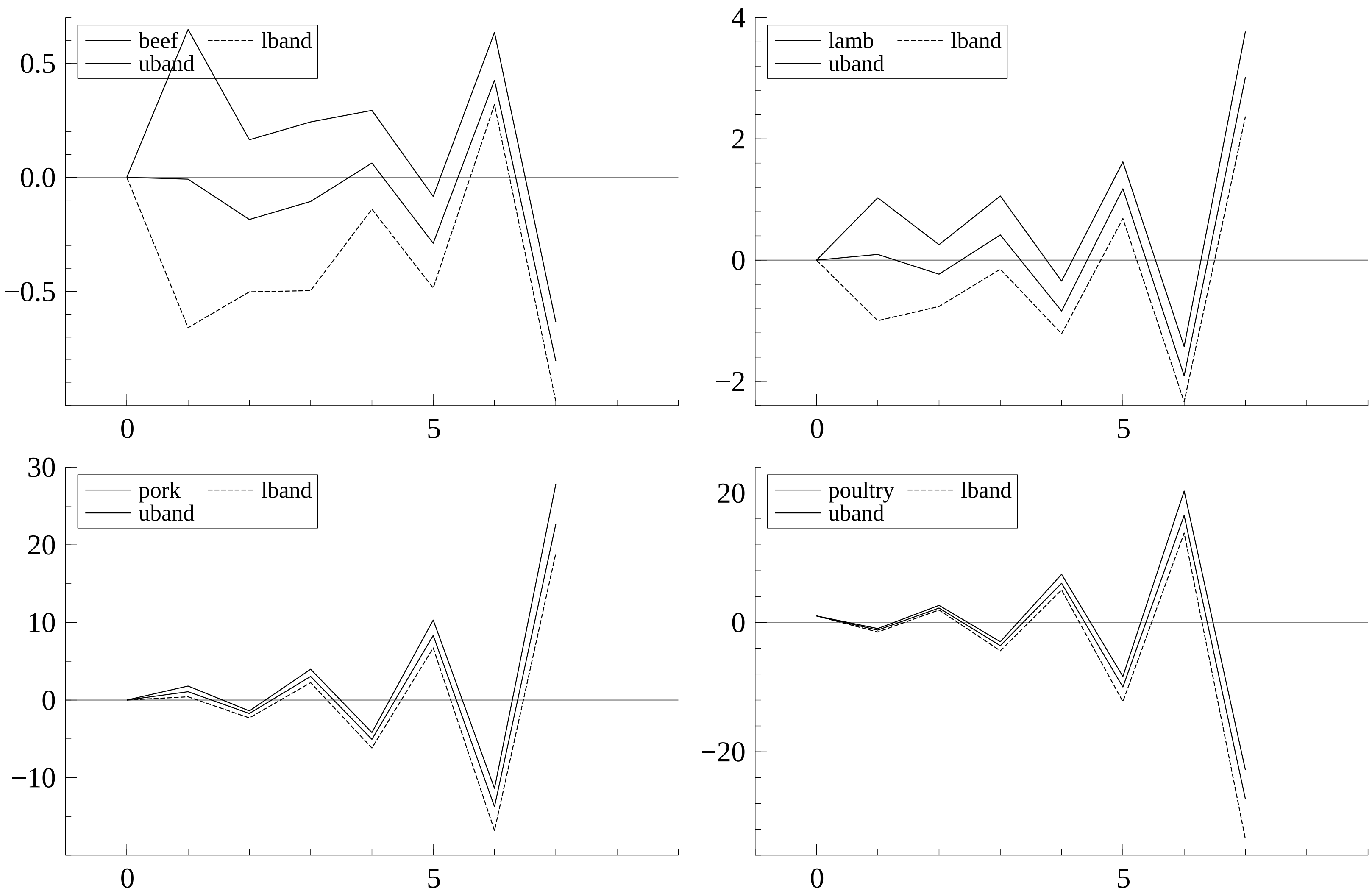




Response of meat consumption to a shock to lamb consumption

Response of meat consumption to a shock to pork consumption





Response of meat consumption to a shock to poultry consumption