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Price Transmission in Sheep Meat Saleyard Markets

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Abstract

There are multiple markets for sheep meat, segmented by age of animal, breed of animal, domestic or export market and type of end product. The different market segments are therefore influenced by a range of supply and demand factors, many of which apply to multiple segments depending on the degree of substitution between animal types possible in the final markets for these products. A relevant question for producers is to what extent are the various sheep meat market segments inter-related. The aim of this paper is to describe the relationships between the prices of six different sheep and lamb categories sold at saleyards in New South Wales. Rather than simple linear models, vector autoregression models (VAR) are used to evaluate these relationships. Results from this study suggest that all sheep meat categories respond significantly to own price shocks. In terms of cross price transmission, restocker and mutton categories are the most responsive to cross price transmission from other sheep meat categories. From an overall sheep meat supply chain perspective, these outcomes suggest that exogenous factors such as adverse climate conditions and changes in the world market are likely the most important to explain volatility in domestic sheep meat prices.

Key words: sheep meat, market segments, price transmission, price volatility, VAR, GARCH

Introduction

In recent weeks the rural press has put a spotlight on sheep meat prices.

'"Farmers are spooked": Why no one wants to buy sheep: Sheep and cattle prices are crashing as supply and demand dynamics pull the rug out from under the industry. And there could be more pain to come.' (Thompson, 2023).

'Sheep prices have been sliding for months, and this week fell to levels not seen in many years. It has been a dramatic downturn in fortunes for sheep producers, who less than three years ago were celebrating record lamb and mutton prices.' (Verley et al., 2023).

Extremely volatile prices are a characteristic of Australian sheep meat markets. In this paper a historical data set of sheep meat prices at the farm level is used to investigate the nature of this instability and the extent to which instability is transmitted from one sheep meat category to another.

The Sheep Meat Industry

The sheep industry is one of the most important in the Australian agricultural sector. In 2021 the sheep flock was almost 68 million head (MLA, 2022), and sheep farming contributed about 5 per cent of agricultural GDP (MLA, 2022). Australia and New Zealand are the major sheep meat suppliers to world markets (MLA, 2022). Overall sheep meat exports from Australia account for about one third of global sheep meat exports (Rural Bank, 2018).

Sheep are kept for wool production and meat production as well as for breeding. In lay terms (the formal definitions relate to the status of the animal's teeth as well as age), a sheep up to 10 months of age is termed a lamb, a sheep from 10 to 18 months old is termed a hogget, while older sheep meat is termed mutton.

The predominant sheep breed in Australia is the Merino. Almost all of the high value wool output is from Merinos. While some Merino lambs are sold for meat, and increasingly Merinos are being bred as a dual-purpose resource, most of Australian lamb production is from crossbreeds. Approximately 18 million lambs are the first-cross progeny of Merino ewes mated with long-wool meat rams such as the Border Leicester (Fogarty et al., 2005). These first-cross ewes are then mated with a terminal sire to produce prime lambs. The terminal sire has a strong and meaty body and grows fast. Examples of such breeds include White Suffolk, Dorset, Southdown, Texel and Hampshire.

In 2021, lamb slaughters reached almost 21 million head (MLA, 2022). Lambs are slaughtered depending on their dressed weight, with lambs between 18-24 kgs dressed weight being prepared for the Australian market. In the same year mutton slaughter was 5.8 million head. Australia produced almost 508,000 tonnes of lamb and 155,000 tonnes of mutton in 2021 (MLA, 2022).

Sheep meat exports have increased over the years with the United States and China being major export markets for both product types. In 2004-05, lamb exports totalled 120,000 tonnes (shipped weight, sw), valued at $700 million (MLA, 2018). Lamb exports have more than doubled since then, reaching 265,000 tonnes (sw) in 2021. Some 66 per cent of lamb production is exported, while some 96 per cent of mutton production is exported. The total export value of all sheep meat exports in 2021 was $4 billion.

Apart from being one of the major exporters, Australia is ranked second worldwide in sheep meat consumption per capita (about 6 kg), following Kazakhstan (OECD, 2018). Over the last two decades, approximately, lamb consumption has been slightly increasing at about 2 per cent a year (MLA, 2022), displaying some resilience to price volatility. Consumption of mutton in the domestic market is minor, reaching approximately 7,500 tonnes in recent years (MLA, 2019).

Lamb prices have been increasing since the 2000s, reaching record levels in 2021 (bottom half of Figure 1) (MLA, 2022). The trade lamb saleyard indicator price reached 853c/kg, while mutton prices averaged 638c/kg. As shown in Figure 1, some of the other lamb categories exceeded the trade lamb average. However, while there has been a steady upward trend in the annual average price, there has also been significant year to year (Figure 1) and within year variability (Figure 2), even when expressed in real terms (Figure 3 below). All of these figures indicate considerable short- term volatility in sheep meat prices.

One of the major reasons for this price volatility has been adverse climate conditions. Between 2001 and 2009 the country experienced the longest, continual period of low rainfall since 1900 that mainly affected a considerable part of Victoria and the Murray-Darling Basin, which are the home for over 20

Figure 1. Australian agriculture GDP, 1975-2022 (constant prices), and national MLA indicator sheep meat prices, 2000-2023 (current prices)

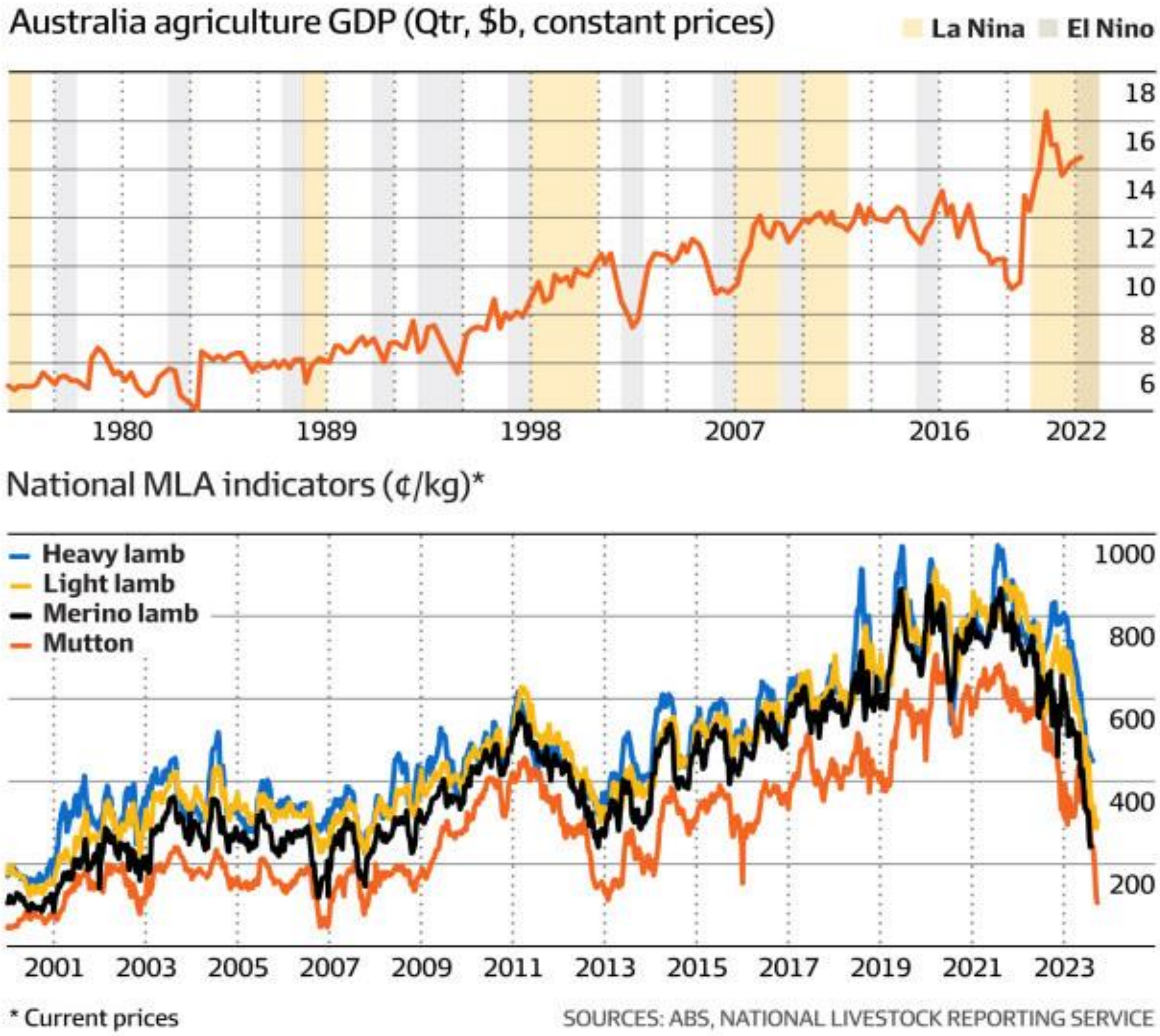
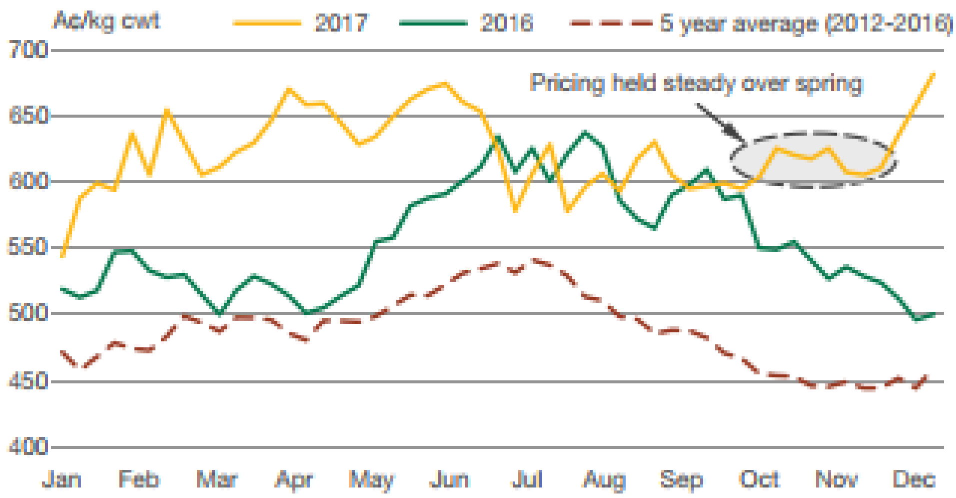


Figure 2. National saleyard trade lamb indicator



Source: MLA (2017)

per cent of the Australian sheep flock (MLA, 2018; van Dijk et al., 2013). Within that period, two major droughts occurred (in 2002/03 and 2006/07) which were reported as the worst ever recorded at that time (top half of Figure 1) (MLA, 2015; van Dijk et al., 2013). According to MLA (2015) the impact of the droughts was associated with high price volatility for sheep meat. Between the two major droughts (2003 and 2007), lamb and mutton prices fell by about 25 and 33 per cent, respectively (MLA, 2015) (bottom half of Figure 1).

At the same time, increasing export demand was also linked to overall price rises, particularly between 2001 and 2002 and beyond 2009 (MLA, 2015). According to MLA (2015) the increasing prices observed between 2013 and 2014 derived mostly from the rising global demand and prices for overall sheep meat, despite the adverse and extreme weather conditions (*La Niña* in 2010/11 and drought in 2013/14) that occurred. Overall, volatility in price for any particular product impacts on the demand for that particular product which, in turn, may have considerable implications for supply in future periods.

This brief overview of the sheep meat industry suggests that there are multiple markets for sheep meat, segmented by age of animal, breed of animal, domestic or export market and type of end product. These markets are characterised in the detailed specifications shown in Appendix 1. The different market segments are therefore influenced by a range of supply and demand factors, many of which apply to multiple segments depending on the degree of substitution between animal types possible in the final markets for these products.

A relevant question for producers is to what extent are the various sheep meat market segments inter-related. For example, a recent issue confronting lamb producers is whether to feed lambs to higher weights to receive higher prices (Ritchie, 2019). One of the key factors is the price of the input (store or restocker lambs), as well as the price of feed and the animal's growth rate, relative to the price of the output (the finished lambs). Richie (2019) reported some simulations of various combinations of these factors and their influence on profitability, but was unable to indicate the most likely scenarios because there was little information available on the way that different lamb and mutton prices move together over time.

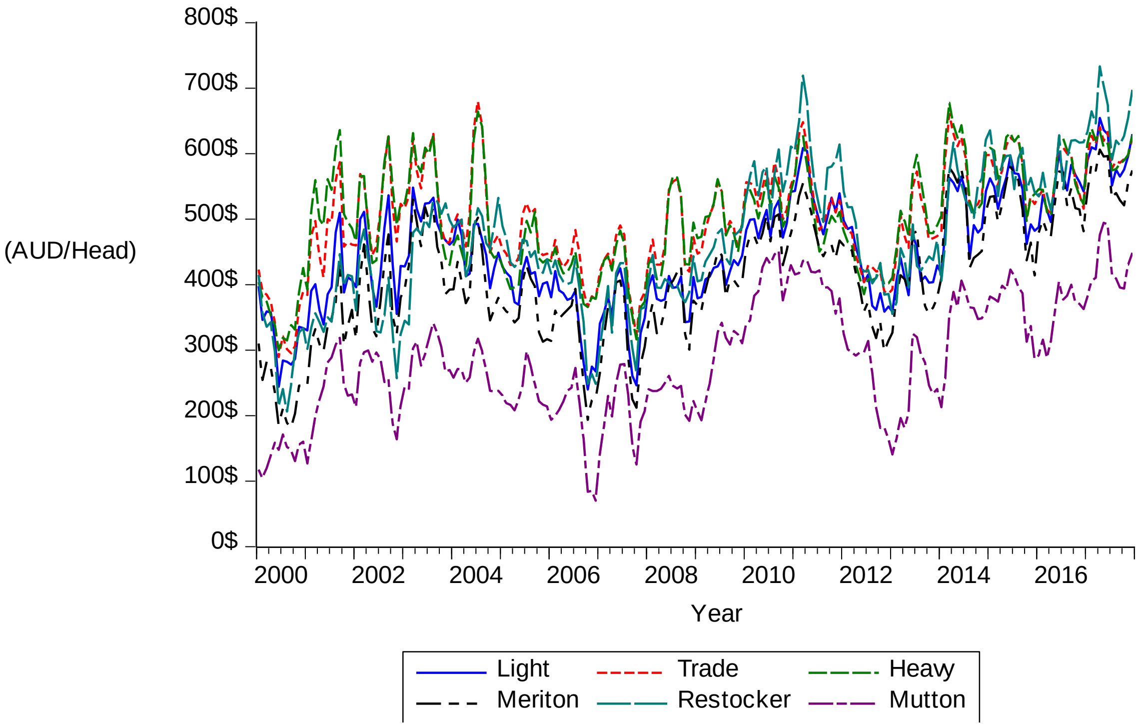
The aim of this paper then is to describe the relationships between the prices of six different sheep and lamb categories sold at saleyards in New South Wales. These six different types of lamb and sheep are the inputs into the various types of lamb and mutton demanded in the market segments shown in Appendix 1. Specifically, this paper assesses price transmission across these sheep meat categories and their volatility. Understanding price dynamics and volatility is relevant, particularly in assisting producers in their decision-making processes.

Data

The six categories of sheep meat assessed in this study are described and abbreviated as following: light weight ("*lght*", between 12 and 18 kg), trade ("*trde*", 18 to 22 kg), heavy ("*heav*", 22+ kg), merino ("*meri*", 16 to 22 kg), restocker (or feeder, "*rstk*", up to 18 kg) and mutton ("*mutt*", 18 to 24 kg). The available saleyard price series for these categories of sheep meat cover the period 2000 to 2017[1] on a monthly basis and are converted to real terms using the seasonally adjusted CPI for lamb (and goat) extracted from the Australian Bureau of Statistics (ABS, 2019). All prices are then used in log-form.

[1] These prices were collected for another purpose during 2018, but they cover a time frame of both excellent and poor seasonal conditions as well as longer run changes in the size of the sheep flock and the growth in export markets.

Figure 3. Real saleyard lamb prices (c/kg), 2000 to 2017



The price series are shown in Figure 3. The same patterns of between year and intra year variability are evident as shown in the bottom half of Figure 1. There is an overall slight upward trend, some cyclical periods of increasing and decreasing prices as well as seasonal patterns.

The variability in these price series is overall high, ranging from about 16 per cent to over 30 per cent. Prices on *trde* and *heav* are the more stable across the series (Table 1). All prices are strongly correlated with each other (Table 2), although *mutt* less so than the other categories.

Table 1. Descriptive statistics of real saleyard lamb prices (c/kg), 2000 to 2017

Lamb category	N	Mean	Std. Dev.	Min	Max	CV (%)
lght	216	448.29	86.81	239.70	654.14	19.36
trde	216	502.04	80.09	289.08	679.95	15.95
heav	216	500.76	83.36	299.79	677.46	16.65
meri	216	411.48	96.26	182.21	605.97	23.39
rstk	216	467.49	107.25	206.07	733.14	22.94
mutt	216	285.79	90.86	69.91	494.22	31.79

Table 2. Correlation matrix of real saleyard lamb prices (c/kg), 2000 to 2017

	lght	*trde*	*heav*	*meri*	*rstk*	*mutt*
lght	1.00	0.97	0.96	0.99	0.98	0.96
trde	-	1.00	0.99	0.98	0.95	0.93
heav	-	-	1.00	0.98	0.93	0.91
meri	-	-	-	1.00	0.96	0.95
rstk	-	-	-	-	1.00	0.95
mutt	-	-	-	-	-	1.00

Method

A number of different methods could be used to examine the relationship between a set of prices. One approach would be to use standard structural econometric modelling to directly estimate price transmission functions (for example, *heav* = f (*trad*, other explanatory variables)). A price transmission elasticity could be derived from the coefficient on the *trad* variable. The 'other explanatory variables' might include various market characteristics, volumes traded, as well as trend and seasonal variables. An alternative might be to estimate a margin type of model, explaining the difference between the two prices directly (for example, *heav* – *trad* = f (other explanatory variables)). Such a model would be similar in style to a typical marketing margin model explaining the difference between prices at different market levels, or a spatial margin model explaining differences between prices in different locations. Such models also require data on those 'other explanatory variables', and in practice most of these models also assume linearity.

Here, data on some of those proposed 'other explanatory variables' are not available, and inspection of the price series shown in Figure 1 and Figure 3 suggests not only that there are a mix of longer run trends and cycles of various lengths, but that the relationships between the various prices vary over time. In this case, a time series approach was considered more appropriate. A vector autoregressive (VAR) model, based on the autoregressive integrated moving average (ARIMA) approach of Box and Jenkins, combined to a generalized autoregressive conditional heteroscedasticity (GARCH) modelling approach is used in this study. The model is estimated at a lag order of two, and the GARCH component is included to account for the time-variant volatility present in the standard VAR (2) model. The model is constructed with price series from 2000 to 2015, and it assumes all the sheep meat prices are jointly endogenous. The period 2016 to 2017 in the dataset is used to assess the model's estimates. The detailed aspects of the model, including the pre-estimation tests, are fully described in Appendix 2.

Results

Price transmission and volatility

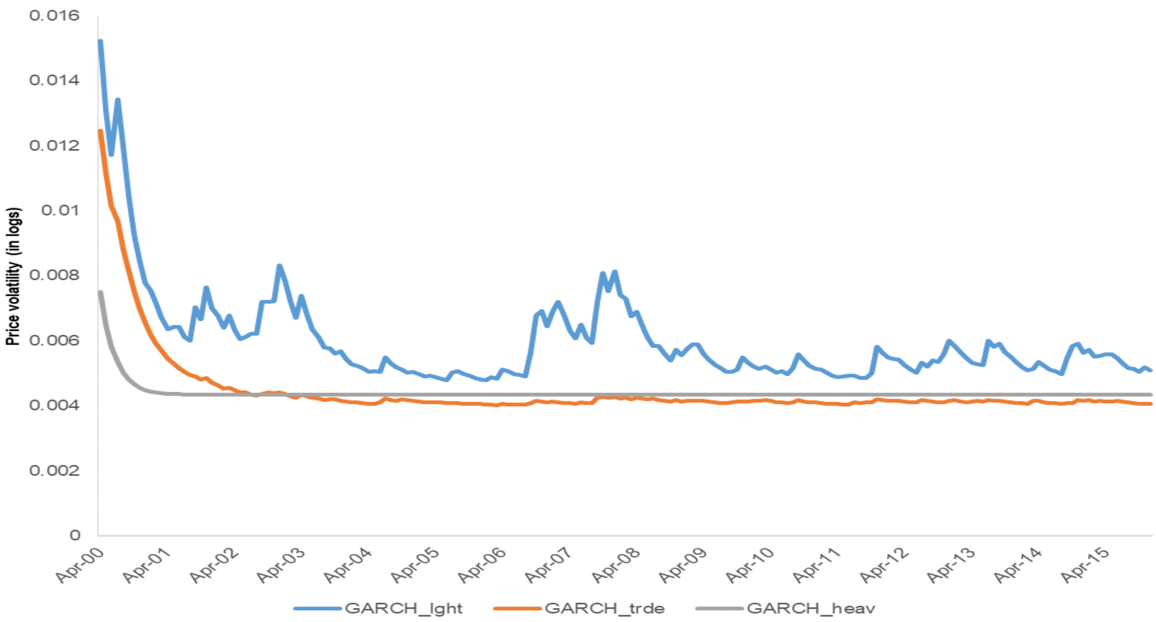
As outlined in Appendix 2, a number of model selection tests were conducted to be able to choose the correct form for the VAR models. It was found that all the VAR (2) models suffer from heteroskedasticity problems, which restricts inference from the coefficients from these models. The full VAR model results are reported in Appendix Table A3.1. Inferences from models with conditional heteroskedasticity can be more efficiently drawn from GARCH models. The full model GARCH results are reported in Appendix Table A3.2. Here, the results displayed focus on the GARCH model outcomes.

As noted in Appendix 2, because there are typically considered to be two broad categories of sheep meat, two variants of Equation 1 are estimated prior to a full model estimation. The first describes the relationship between the three prime lamb categories (light, trade and heavy), and the second describes the relationship between the other categories (merino, restocker and mutton). Then the full VAR model is estimated to describe the relationship between all sheep meat categories.

Prime lamb categories

In Figure 4 is shown the price volatility for the three categories of prime lamb based on the model with three endogenous regressors. Over the period 2000 to 2015, *lght* volatility was the highest across the three lamb meat categories. The periods with higher volatility (e.g., 2001 – 2003 and 2006 – 2007) – as suggested by *lght* in Figure 3 – reflect the significant shocks which were described earlier (MLA, 2015).

Figure 4. Price volatility for prime lamb categories (2000 to 2015)



The higher volatility for *lght* can be explained by its responsiveness to shocks in prices from other lamb meat categories. This is shown in Table 3. In the GARCH model, parameters from the B matrix represent volatility transmission within each series, i.e, the volatility in one price series caused by a shock in that series, while parameters from the A matrix represent volatility transmission across the series, i.e., the volatility in one price series caused by a shock in other price series (Serra, Zilberman, and Gil, 2010). The GARCH model (Equation (3) in Appendix 2) can be used to test the impulse response on the volatility of different price series based on simulated shocks introduced to each price series.

Table 3. GARCH (1,1) estimated parameters for prime lamb categories

	Coefficient	Std. Error	Prob.
M(1,1) *(lght)*	0.00095	0.00036	0.0087
M(2,2) *(trde)*	0.00060	0.00015	0.0001
M(3,3) *(heav)*	0.00138	0.00055	0.0123
A1(1,1) *(lght)*	0.19114	0.05496	0.0005
A1(2,2) *(trde)*	0.08294	0.06160	0.1782
A1(3,3) *(heav)*	0.02113	0.07870	0.7883
B1(1,1) *(lght)*	0.89089	0.03823	0.0000
B1(2,2) *(trde)*	0.92081	0.02042	0.0000
B1(3,3) *(heav)*	0.82579	0.07626	0.0000

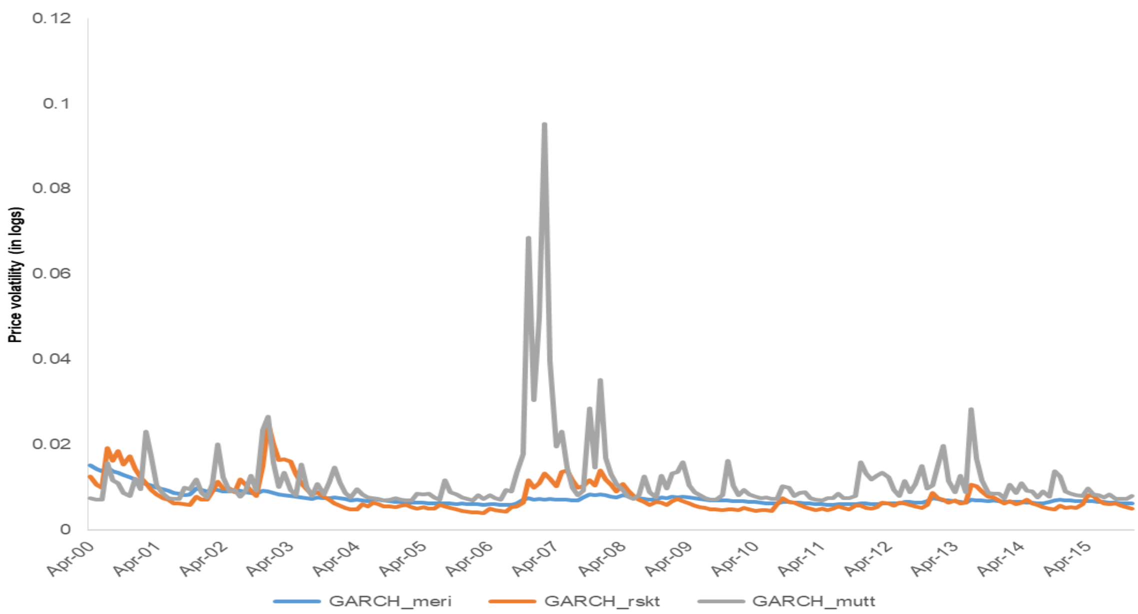
As shown in matrix B in Table 3, price volatility from all the three lamb meat categories is strongly responsive to own price shocks. For example, a 1 per cent change in the price for *trde* causes about 0.9 per cent change in the price for *trde* in subsequent periods.

But *lght* is the only price that displays a significant coefficient (0.19) from matrix A. This suggests that a 1 per cent change in the price for *trde* or *heav* (or both) causes about 0.19 per cent change in the price for *lght*. *Lght* is the only category that reacts to volatility changes in other categories of lamb meat. So, if price volatility for other categories of prime lamb change, it is expected that the price volatility for *lght* would change significantly in the same direction.

Merino, restocker and mutton

When looking to the other sheep meat category, it can be seen that *mutt* and *rstk* are relatively more volatile than *meri* (Figure 5). As shown, the peak in price volatility for *rstk* is observed around 2003, the period where the first of two extreme droughts occurred between 2001 and 2009 was registered. During that time, *mutt* also experienced a similar magnitude in price volatility. Around 2007, however, price volatility in *mutt* reached its peak. This was the period the second severe drought was observed. Since mid/late 2008 onwards, *mutt* volatility remained higher and more unstable across these three sheep meat categories. Since nearly 95 per cent of the mutton meat is exported (MLA, 2019), the volatility shown is likely to result from the impact of exogenous shocks from the world market referred to by MLA (2015). In contrast, volatility for *meri* remained at about the average level volatility for *rstk*.

Figure 5. Price volatility for other lamb categories (2000 to 2015)



As shown in matrix B in Table 4, price volatility from all the three other lamb categories is strongly responsive to own price shocks. For example, a 1 per cent change in the price for *meri* causes about 0.95 per cent change in the price for *meri* in subsequent periods. The coefficients for the *meri* and *rstk* categories are at similar levels as for the prime lamb categories, but the coefficient for the *mutt* category is substantially less at 0.6.

In terms of price volatility relationships across the category, these three lamb types all respond significantly and positively to price changes in any of the other categories. Overall, responsiveness is higher for *mutt* and lower for *meri*. As the coefficients from Table 4 suggest, a 1 per cent increase in prices for either *meri* or *rstk* (or both), is likely to increase *mutt* price by about 0.5 per cent. Thus, based on this model with three endogenous regressors, *mutt* is less responsive to own price shocks than *meri* and *rstk* but more responsive to external shocks.

Table 4. GARCH (1,1) estimated parameters for other lamb categories

	Coefficient	Std. Error	Prob.
M(1,1) *(meri)*	0.00054	0.00019	0.0050
M(2,2) *(rstk)*	0.00080	0.00035	0.0225
M(3,3) *(mutt)*	0.00436	0.00097	0.0000
A1(1,1) *(meri)*	0.14905	0.04557	0.0011
A1(2,2) *(rstk)*	0.33612	0.04849	0.0000
A1(3,3) *(mutt)*	0.50199	0.05932	0.0000
B1(1,1) *(meri)*	0.94702	0.01495	0.0000
B1(2,2) *(rstk)*	0.87824	0.03501	0.0000
B1(3,3) *(mutt)*	0.59862	0.07963	0.0000

Full model with the six sheep meat categories

Looking at the outcomes from the full model, price volatility for all sheep meat categories displays similar behaviour as for the subsets of categories. The only exception is price volatility for *lght* that is now apparently stable (Figure 6). This, however, is likely to be due to the change in scale influenced by the magnitude of price volatility for *mutt* and *rstk* (see the left-hand axes of Figure 4 and Figure 5).

Overall outcomes from the full model are consistent with previous "partial models" in suggesting that all sheep meat prices respond significantly to own price shocks (Table 5). The coefficients of matrix B are of similar magnitude to those of the partial models. The only coefficient that increased considerably is the one for *mutt* that jumped from about 0.60 to nearly 0.74.

However, the coefficients from matrix A in the full GARCH model are lower compared to the partial models. In some instances, coefficients are even negative (Table 5). This is the case for the cross-price volatility transmission (matrix A) coefficients for *trde* and *heav*, although only the coefficient for *heav* showed significant at the 5 per cent level. Linking to previous results shown in Table 3, this suggests that increasing prices for *meri*, *rstk* or *mutt* (or more than one of these categories) tend to lower prices for *heav* lambs.

Price shocks

Price shocks to each price series are introduced to assess impulse response across all price series. This can be viewed as a complementary assessment from the results reported above. Impulse response from each price series is tested from shocks introduced in own prices and prices from other sheep meat categories in separate simulations.

The full model with data from 2000 to 2017 is used to assess impulse responses and a 10 per cent shock is introduced in price forecast for January 2019. From this period, volatility is stable for most price series in the absence of any price shock. Results from price volatility responsiveness to price shocks are displayed in Figure 7.

Figure 6. Price volatility for all sheep meat categories (2000 to 2015)

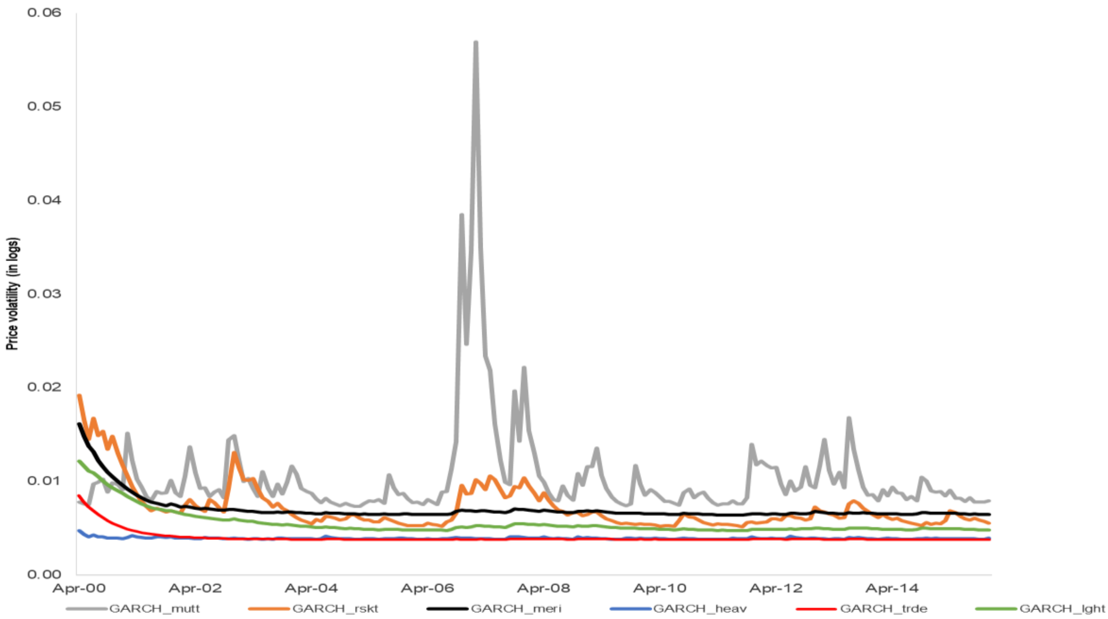
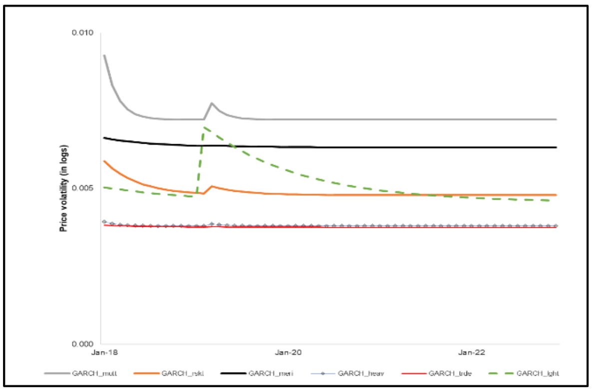


Table 5. GARCH (1,1) estimated parameters for the full model

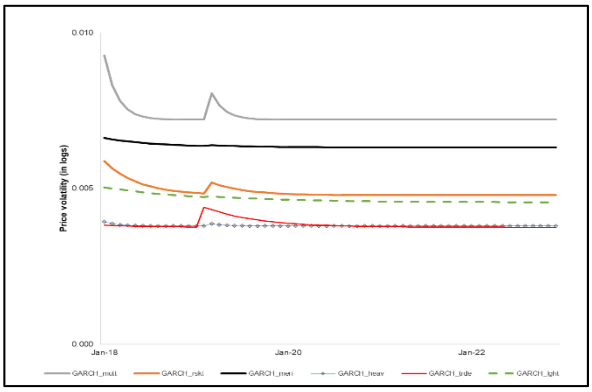
	Coefficient	Std. Error	Prob.
M(1,1) *(lght)*	0.00035	0.00011	0.0017
M(2,2) *(trde)*	0.00051	0.00012	0.0000
M(3,3) *(heav)*	0.00169	0.00091	0.0643
M(4,4) *(meri)*	0.00085	0.00029	0.0029
M(5,5) *(rstk)*	0.00096	0.00036	0.0075
M(6,6) *(mutt)*	0.00326	0.00117	0.0054
A1(1,1) *(lght)*	0.07771	0.03193	0.0150
A1(2,2) *(trde)*	-0.04127	0.03613	0.2534
A1(3,3) *(heav)*	-0.10891	0.05320	0.0406
A1(4,4) *(meri)*	0.07591	0.03631	0.0365
A1(5,5) *(rstk)*	0.23221	0.03956	0.0000
A1(6,6) *(mutt)*	0.35311	0.06050	0.0000
B1(1,1) *(lght)*	0.96077	0.01115	0.0000
B1(2,2) *(trde)*	0.92936	0.01458	0.0000
B1(3,3) *(heav)*	0.74484	0.15161	0.0000
B1(4,4) *(meri)*	0.93040	0.02141	0.0000
B1(5,5) *(rstk)*	0.89366	0.02771	0.0000
B1(6,6) *(mutt)*	0.73839	0.08409	0.0000

Outcomes from Figure 7 show that price volatility due to cross price transmission is higher for *rstk* and *mutt*. It seems to be higher from shocks on *trde*. Nonetheless, price volatility from these two (*rstk* and *mutt*) is more responsive to own price shocks, which is unlikely transmitted to other sheep meat categories. Overall volatility due to cross price transmission is very marginal to other sheep meat categories. This is also confirmed from the coefficients in Table 5. Despite being significant at 5 per cent, the magnitude of coefficients for cross price transmission is very low for the other four sheep meat categories compared to *rstk* and *mutt*. These outcomes overall suggest that only *rstk* and *mutt* producers are likely to suffer higher price volatility due to shocks on any other sheep meat category. A related suggestion is that the *meri* category is now more closely linked with the prime lamb types, due to the focus on dual purpose genetics improvements.

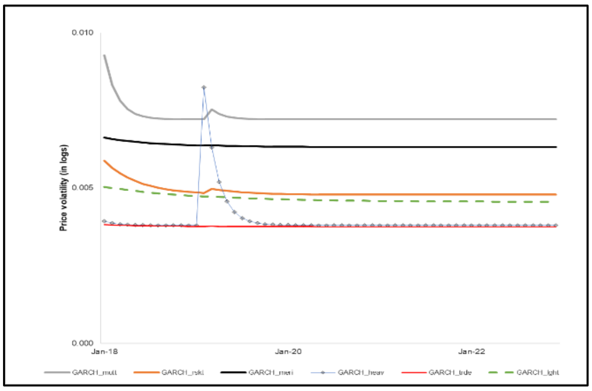
Figure 7. Price shocks and volatility transmission



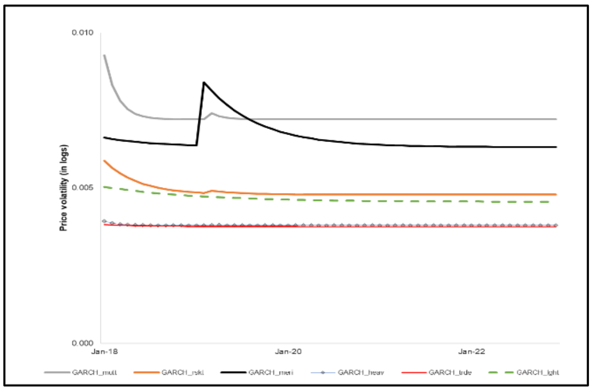
(a) Shocks to "lght"



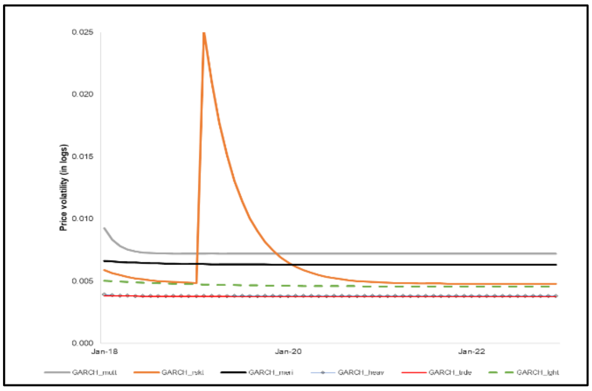
(b) Shocks to "trde"



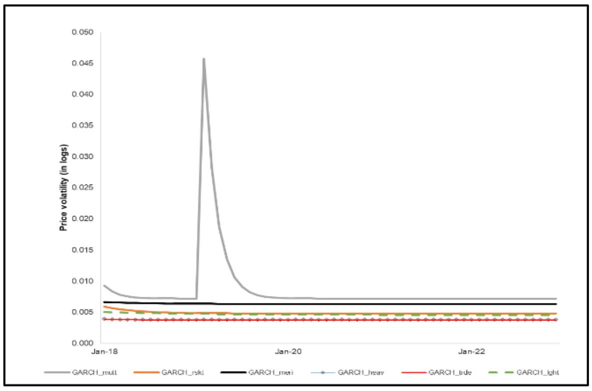
(c) Shocks to "heav"



(d) Shocks to "meri"



(e) Shocks to "rstk"



(f) Shocks to "mutt"

From an overall Australian sheep meat supply chain perspective, these outcomes suggest that exogenous factors such as adverse climate conditions and changes in the world market are likely the most important to explain volatility in domestic sheep meat saleyard prices. This is at least the case to sheep meat prices in New South Wales. Volatility due to cross price transmission is very marginal in most cases, suggesting that overall sheep meat categories belong to very segmented and unlikely strongly related markets. The only exceptions are to *trde* and *rstk* and *trde* and *mutt* relationships.

Restocker and mutton sheep meat producers are the only ones likely to be strongly impacted by exogenous factors that impact on domestic prices for trade lamb meat.

Conclusion

In general, results from this study suggest that all sheep meat categories respond significantly to own price shocks. In terms of cross price transmission, restocker and mutton are the most responsive to cross price transmission from other sheep meat categories. Nonetheless, cross price transmission between the two is unlikely to occur. Cross price transmission is apparently higher from trade to restocker and mutton. Overall, volatility due to cross price transmission is marginal, in spite of strong correlation coefficients between the prices. This suggests that, at least at the saleyard, sheep meat markets look more like very segmented and unlikely strongly related markets.

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Appendix 1. Sheep Meat Market Specifications

Table A1.1. Domestic Lamb

Market segment	Carcase weight (kg)	Preferred fat scores	Comment
Supermarket lamb	18 to 22	2 and 3	Second cross preferred
Food service lamb	20 to 25	2 and 3	Lean and high yielding preferred
Other domestic lamb	Variable weights	2 to 4	Range of lamb types depending on end user requirements

Source: MLA 'The Lamb Guide'. Note: MSA prefers a fat score of 2-3

Table A1.2. Export lamb

Market segment	Carcase weight (kg)	Preferred fat score	Comment
Heavy export	20 to 30	2 to 4	North America for prime cuts. Large volume markets for lower value cuts
Light export	10 to 16	2	Mainly Middle Eastern markets
'Haj' market	35 to 41 liveweight		Market is for lambs (6 to 12 months). Entire male animals with 'long' tail intact are preferred

Source: MLA 'The Lamb Guide'

Table A1.3. Domestic markets for hogget and mutton

Market segment	Comment
Domestic manufacturing	17 to 21kg carcase weight, fat class 1 to 3, for manufactured meat products
Domestic retail	Hogget sold through meat retailers
Domestic food service	Cuts used in Asian and Middle Eastern style restaurants

Source: MLA 'Making the Most of Mutton' (Publication LPI061)

Table A1.4. Export markets for hogget and mutton

Market segment	Carcase weight (kg)	Preferred fat class	Comment
Heavy export	More than 20	2 to 4	Heavy carcase weights preferred
Light export	14 to 16	1 to 2	Lightweight, lean carcases
Live sheep	NA	NA	Wethers more than 50 kg liveweight

Source: MLA 'Making the Most of Mutton' (Publication LPI061)

Appendix 2. Details of the Method and Statistical Test Results

A vector autoregressive (VAR) modelling is the basic approach used in this study. VAR and its variant (the vector error correction) are typically the most common econometric models used for price transmission analyses. The general form of the VAR used in this study is described as Equation 1 below, which follows the standard form described by Enders (2015). Equation 1 is extended to capture seasonality, as in the model by Popat, Griffith, and Mounter (2017).

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \cdots + \alpha_p y_{t-p} + \beta_z d_{z,t} + \varepsilon_t \qquad (1)$$

where,

p = is the lag length;
y_t = a (n x 1) vector of endogenous variables (sheep meat prices);
α_0 = a (n x 1) vector of intercept terms;
α_i = p (n x n) matrices of the unknown parameters for the endogenous regressors (i = 1, 2, …, p);
β = a (n x 1) vector of the unknown parameters for the dummy variables;
d_t = a (z x 1) vector of dummy variables (z = 1, 2, …, 12; from January to November and for the years where droughts have been reported, i.e., 2001 to 2009 and 2013 to 2014, respectively);
ε_t = a (n x 1) vector of error terms (assumed to be white noise).

To interpret Equation 1, the current price of each sheep meat category is explained by its own past values and the past prices of related categories, up to lag length p, and dummy variables to account for seasonality and periods of extreme drought. Statistical tests are conducted to inform choices about lag length and particular modelling procedures.

The full model of Equation 1 is estimated with six endogenous regressors that account for the different sheep meat categories, which include the three categories of prime lamb (based on weight: light, trade and heavy), and three other sheep meat categories (merino, restocker and mutton). These categories are based on meat grading attributes. For instance, whilst lamb is mainly produced for meat, merino's main purpose is wool production, being its meat a by-product (Dalgleish and Agar, 2017). Therefore, meat quality attributes are likely to differ considerably between these two categories. This also occurs for restocker (whose main purpose is for future breeding or to be re-fattened) and mutton, which refers to sheep over 10 months old that cannot be classified as lamb (MLA, 2017).

Because of these two broad categories of sheep meat, two variants of Equation 1 are estimated prior to a full model estimation. The first describes the relationship between the three prime lamb categories (light, trade and heavy), and the second describes the relationship between the other categories (merino, restocker and mutton). Then the full VAR model is estimated to describe the relationship between all sheep meat categories.

The VAR models in this study are estimated using Eviews 10. Parameters from the VAR are consistently estimated using the ordinary least squares estimator, and estimates are consistent and efficient asymptotically subject to residuals being white-noise processes (Enders, 2015; Popat et al., 2017).

Preliminary observations

In general, VAR models are recommended for stationary series (Enders, 2015). Diagnosis tests on the data – using the Augmented-Dickey-Fuller (ADF) and Phillips-Perron tests – indicate that all of the price series (with only one exception – rstk, significant at the 10 per cent level) are indeed stationary at the 5 per cent significance level, when at least an intercept is accounted for in each price series

(Table A2.1). In the case of agricultural commodities where prices are usually correlated (at least) with their own lagged observations, a pure random walk process (without an intercept or trend) for the stationary test can be misleading.

Table A2.1. Stationary tests

		ADF (p-value)	Phillips-Perron (p-value)
	Intercept	0.022**	0.017**
lght	Intercept and trend	0.0067***	0.0040***
	None [a]	0.75	0.75
	Intercept	0.00020***	0.0018***
trde	Intercept and trend	0.00010***	0.0014***
	None	0.75	0.74
	Intercept	0.00010***	0.0022***
heav	Intercept and trend	0.00010***	0.0026**
	None	0.75	0.75
	Intercept	0.0036***	0.016**
meri	Intercept and trend	0.00040***	0.0027***
	None	0.76	0.75
	Intercept	0.053*	0.051*
rstk	Intercept and trend	0.004***	0.0031***
	None	0.76	0.76
	Intercept	0.0019***	0.012**
mutt	Intercept and trend	0.0011***	0.011**
	None	0.79	0.80

Significant at 10% (*), 5% (**) and 1% (***). [a] Data displayed in Figure 3 suggest that an intercept and a trend should be accounted for the stationary test in all price series

All variants of Equation 1 are initially estimated at one lag order (VAR(1)) as suggested by the Schwarz Bayesian (SC) and Hannan-Quinn (HQ) criteria (Table A2.2). However, due to issues with serial autocorrelation (Table A2.3, where the LM statistic is significant for lag 1), the models are re-estimated as VAR(2). A 2-period lag is the optimal lag length suggested by the Akaike (AIC) and final prediction error (FPE) tests in Table A2.2, and for the SC and HQ criteria, the test statistics for lags 1 and 2 are little different.

Preliminary assessment of the outcomes from the VAR(2) using the Lagrange Multiplier (LM) test at the 5 per cent level show that the three models do not fail to reject the null hypothesis of no autocorrelation (Table A2.4). However, results from the White test at the 5 per cent level point to the presence of time-variant volatility in each model (Table A2.5). In such cases, though coefficients from the models can still be consistent, inference as well as other post estimation tests (e.g., impulse response tests and forecasting) may not be valid (Brüggemann, Jentsch, and Trenkler, 2016; Hill, Griffiths, and Lim, 2012). In VAR models, post-estimation impulse response tests are usually of primary interest and are applied to assess the response of each endogenous variable to own shocks and shocks to other regressors (Popat et al., 2017). Since these kinds of assessment, as well as forecasting, are objectives of this study, VAR models that account for conditional heteroskedasticity are appropriate.

To account for this heteroskedasticity problem, the VAR(2) models are combined into a generalized autoregressive conditional heteroskedasticity (GARCH) modelling approach. One of the main advantages of GARCH is the ability to forecast values with less variability compared to unconditional heteroskedasticity models such as Equation (1) (Enders, 2015; Hill et al., 2012).

Table A2.2. Lag order selection

Endogenous variables: LOG_LGHT_CPI LOG_TRDE_CPI LOG_HEAV_CPI LOG_MERI_CPI LOG_RSTK_CPI LOG_MUTT_CPI
Exogenous variables: C DD1 DD2 DD3 DD4 DD5 DD6 DD7 DD8 DD9 DD10 DD11 DRGHT
Sample: 2000M01 2015M12
Included observations: 184

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1291.672	NA	7.53e-14	-13.19208	-11.82923	-12.63970
1	1903.781	1097.804	1.44e-16	-19.45414	-17.46228*	-18.64681*
2	1955.534	89.44376	1.22e-16*	-19.62537*	-17.00450	-18.56310
3	1987.793	53.64700	1.28e-16	-19.58470	-16.33482	-18.26749
4	2008.728	33.45124	1.53e-16	-19.42096	-15.54207	-17.84880
5	2047.033	58.70706*	1.52e-16	-19.44602	-14.93812	-17.61891
6	2080.282	48.78854	1.61e-16	-19.41611	-14.27920	-17.33405
7	2116.531	50.82731	1.66e-16	-19.41881	-13.65290	-17.08182
8	2152.523	48.12010	1.74e-16	-19.41873	-13.02380	-16.82679

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

Table A2.3. Autocorrelation test (full VAR(1) model)

VAR Residual Serial Correlation LM Tests
Null Hypothesis: no serial correlation at lag order h
Sample: 2000M01 2015M12
Included observations: 191

Lags	LM-Stat	Prob
1	93.30340	0.0000
2	28.05866	0.8251
3	61.27224	0.0054
4	46.13369	0.1201
5	38.72298	0.3478
6	57.98636	0.0115
7	43.66166	0.1780
8	45.23375	0.1392
9	50.65290	0.0534
10	54.99267	0.0222
11	40.25266	0.2875
12	45.16539	0.1407

Probs from chi-square with 36 df.

Table A2.4. Autocorrelation tests from the VAR(2) (partial and full models)

a. Lamb meat model

VAR Residual Serial Correlation LM Tests
Sample: 2000M01 2015M12
Included observations: 190

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	15.70322	9	0.0733	1.763571	(9, 404.2)	0.0734
2	12.41895	9	0.1907	1.389087	(9, 404.2)	0.1907
3	10.17919	9	0.3362	1.135427	(9, 404.2)	0.3362
4	12.87815	9	0.1682	1.441266	(9, 404.2)	0.1682
5	7.233828	9	0.6128	0.803970	(9, 404.2)	0.6128
6	15.54146	9	0.0771	1.745056	(9, 404.2)	0.0771
7	16.32495	9	0.0604	1.834804	(9, 404.2)	0.0604
8	15.23967	9	0.0846	1.710532	(9, 404.2)	0.0846

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	15.70322	9	0.0733	1.763571	(9, 404.2)	0.0734
2	20.78058	18	0.2906	1.160294	(18, 461.5)	0.2908
3	32.86081	27	0.2017	1.226881	(27, 467.9)	0.2020
4	50.55895	36	0.0544	1.428513	(36, 464.6)	0.0547
5	65.38648	45	0.0251	1.486942	(45, 458.3)	0.0254
6	75.39076	54	0.0288	1.430081	(54, 450.7)	0.0293
7	88.00129	63	0.0205	1.436230	(63, 442.6)	0.0210
8	118.6966	72	0.0004	1.735916	(72, 434.2)	0.0005

*Edgeworth expansion corrected likelihood ratio statistic.

b. Other sheep meat model

VAR Residual Serial Correlation LM Tests
Sample: 2000M01 2015M12
Included observations: 190

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	11.62217	9	0.2355	1.298689	(9, 404.2)	0.2355
2	13.79960	9	0.1296	1.546146	(9, 404.2)	0.1297
3	7.338841	9	0.6019	0.815747	(9, 404.2)	0.6019
4	14.71954	9	0.0989	1.651092	(9, 404.2)	0.0990
5	10.65143	9	0.3004	1.188795	(9, 404.2)	0.3004
6	13.26742	9	0.1509	1.485544	(9, 404.2)	0.1509
7	7.566650	9	0.5783	0.841304	(9, 404.2)	0.5784
8	8.299238	9	0.5043	0.923590	(9, 404.2)	0.5043

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	11.62217	9	0.2355	1.298689	(9, 404.2)	0.2355

2	21.43834	18	0.2579	1.197865	(18, 461.5)	0.2580
3	31.00169	27	0.2711	1.155208	(27, 467.9)	0.2714
4	50.65439	36	0.0534	1.431353	(36, 464.6)	0.0537
5	62.03620	45	0.0467	1.405728	(45, 458.3)	0.0472
6	73.59596	54	0.0393	1.393342	(54, 450.7)	0.0399
7	84.40177	63	0.0373	1.372095	(63, 442.6)	0.0381
8	94.48818	72	0.0390	1.345365	(72, 434.2)	0.0403

*Edgeworth expansion corrected likelihood ratio statistic.

c. Full model

VAR Residual Serial Correlation LM Tests
Null Hypothesis: no serial correlation at lag order h
Sample: 1 192
Included observations: 190

Lags	LM-Stat	Prob
1	49.56278	0.0656
2	58.30466	0.0107
3	46.97669	0.1041
4	41.53598	0.2421
5	37.90376	0.3825
6	49.03052	0.0724
7	34.18325	0.5552
8	34.36635	0.5464
9	49.46294	0.0668
10	50.94891	0.0505
11	37.39334	0.4049
12	40.21315	0.2890

Probs from chi-square with 36 df.

Table A2.5. Heteroskedasticity tests from the VAR(2) (partial and full models)

a. Lamb meat model

VAR Residual Heteroskedasticity Tests (Includes Cross Terms)
Sample: 2000M01 2015M12
Included observations: 190

Joint test:

Chi-sq	df	Prob.
867.0415	732	0.0004

Individual components:

Dependent	R-squared	F(122,67)	Prob.	Chi-sq(122)	Prob.
res1*res1	0.722976	1.433249	0.0531	137.3654	0.1617
res2*res2	0.748788	1.636945	0.0138	142.2698	0.1013
res3*res3	0.680448	1.169415	0.2422	129.2852	0.3086
res2*res1	0.723508	1.437060	0.0518	137.4665	0.1603
res3*res1	0.696506	1.260347	0.1494	132.3362	0.2463
res3*res2	0.716596	1.388617	0.0701	136.1531	0.1800

b. Other sheep meat model

VAR Residual Heteroskedasticity Tests (Includes Cross Terms)
Sample: 2000M01 2015M12
Included observations: 190

Joint test:

Chi-sq	df	Prob.
874.6479	732	0.0002

Individual components:

Dependent	R-squared	F(122,67)	Prob.	Chi-sq(122)	Prob.
res1*res1	0.779245	1.938556	0.0017	148.0565	0.0543
res2*res2	0.844655	2.986042	0.0000	160.4844	0.0111
res3*res3	0.885131	4.231728	0.0000	168.1748	0.0036
res2*res1	0.826974	2.624791	0.0000	157.1250	0.0177
res3*res1	0.827600	2.636314	0.0000	157.2439	0.0174
res3*res2	0.829575	2.673239	0.0000	157.6193	0.0165

c. Full model

VAR Residual Heteroskedasticity Tests: No Cross Terms (only levels and squares)
Sample: 1 192
Included observations: 190

Joint test:

Chi-sq	df	Prob.
1079.416	756	0.0000

Individual components:

Dependent	R-squared	F(36,153)	Prob.	Chi-sq(36)	Prob.
res1*res1	0.319925	1.999306	0.0020	60.78566	0.0060
res2*res2	0.291553	1.749039	0.0107	55.39511	0.0204
res3*res3	0.282833	1.676092	0.0169	53.73820	0.0289
res4*res4	0.327955	2.073983	0.0012	62.31148	0.0042
res5*res5	0.339392	2.183465	0.0006	64.48443	0.0025
res6*res6	0.529333	4.779730	0.0000	100.5732	0.0000
res2*res1	0.271754	1.585942	0.0293	51.63330	0.0442
res3*res1	0.245323	1.381545	0.0927	46.61130	0.1108
res3*res2	0.285456	1.697847	0.0148	54.23659	0.0261
res4*res1	0.321313	2.012095	0.0019	61.04955	0.0057
res4*res2	0.275883	1.619214	0.0240	52.41769	0.0378
res4*res3	0.231936	1.283394	0.1521	44.06786	0.1672
res5*res1	0.320065	2.000594	0.0020	60.81228	0.0060
res5*res2	0.279584	1.649368	0.0200	53.12092	0.0328
res5*res3	0.250519	1.420593	0.0753	47.59868	0.0935
res5*res4	0.349739	2.285833	0.0003	66.45034	0.0015
res6*res1	0.471427	3.790518	0.0000	89.57115	0.0000
res6*res2	0.327319	2.068002	0.0013	62.19061	0.0043

res6*res3	0.242054	1.357261	0.1052	45.99030	0.1230
res6*res4	0.412247	2.980926	0.0000	78.32689	0.0001
res6*res5	0.437461	3.305038	0.0000	83.11767	0.0000

Acknowledging that residuals from the VAR(2) models are time-variant processes, a GARCH process is about modelling these residuals conditional to their past information as described in equations (2) and (3). Equation (3) is the general GARCH (*p, q*) model under the BEKK[2] representation. Compared to alternatives, this representation has particular advantages such as estimating a reduced number of parameters and ensuring positive semi definite time covariance matrices (Bauwens et al., 2006; Bergmann, O'connor, and Thümmel, 2017; Engle and Kroner, 1995; Musunuru, 2014).

$$\varepsilon_t = {H_t}^{0.5} v_t \tag{2}$$

$$H_t = \mathrm{M}'\mathrm{M} + \sum_{i=1}^{p} A'_i(\varepsilon_{t-i}, \varepsilon'_{t-i})A_i + \sum_{j=1}^{q} B'_j H_{t-j} B_j \tag{3}$$

where,

M = is the lower triangle matrix of parameters;
A = is the unrestricted square matrix of parameters A_i (i = 1, 2, …, p);
B = is the unrestricted square matrix of parameters B_j (i = 1, 2, …, q);
H_t = is the conditional covariance matrix;
q = is the number of lagged squared-error terms;
v_t = an (n x 1) vector of standard residuals (assumed to be white noise).

For each VAR(2) model with heteroskedastic error terms, a GARCH (1,1) model is estimated, which is the most common representation and it is regarded as a sufficient and parsimonious representation to capture the volatility in many data series (Brooks, 2008; Engle and Kroner, 1995; Hill et al., 2012; Lütkepohl and Netšunajev, 2017). GARCH models can be consistently estimated using the maximum likelihood estimator or quasi-maximum likelihood estimator (Bauwens et al., 2006; Bergmann et al., 2017; Engle and Kroner, 1995; Hill et al., 2012; Laurent, Rombouts, and Violante, 2012; Musunuru, 2014; Rezitis and Stavropoulos, 2012). For simplicity, in this study a maximum likelihood estimator is used.

Impulse responses from the conditional heteroskedastic VAR models can be assessed through parameters from the respective GARCH component. In Equation (3), parameters from the A matrix represent volatility transmission across the series, i.e., the volatility in one price series caused by a shock in other price series, while parameters from the B matrix represent volatility transmission within each series (Serra, Zilberman, and Gil, 2010). Equation (3) is then used to test the impulse response on the volatility of different price series based on simulated shocks introduced to each price series.

A number of studies have used multivariate GARCH models in price transmission analysis relating to agricultural commodities (Bergmann et al., 2017; Musunuru, 2014; Rezitis and Stavropoulos, 2012; Serra et al., 2010). Serra et al. (2010) and Bergmann et al. (2017) are some examples that combined a multivariate GARCH approach to a vector error correction model.

Parameters from the full VAR(2) model are used to forecast lamb prices in order to assess impulse responses on price volatilities under the GARCH approach. All the VAR(2) models are constructed with

[2] For more details about this and other representations of the GARCH process, readers can refer to Engle and Kroner (1995) and Bauwens, Laurent, and Rombouts (2006).

data from 2000 to 2015. Data from 2016 and 2017 are used to assess the full VAR(2) model's mean absolute percentage error (MAPE) in prediction. The period 2018 and 2022 is then considered for price forecasting and impulse response tests. Due to limitations in Eviews 10, a Microsoft Excel spreadsheet is used to forecast lamb prices and volatilities, based on estimated VAR(2) GARCH equations.

The full model VAR(2) and GARCH model outputs are shown in Appendix 3 for interested readers.

Appendix 3. Full Model Results

Table A3.1. Full VAR(2) model estimation outputs

Vector Autoregression Estimates
Sample (adjusted): 3 192
Included observations: 190 after adjustments
Standard errors in ( ) and t-statistics in [ ]

	LOG_LGHT_CPI	LOG_TRDE_CPI	LOG_HEAV_CPI	LOG_MERI_CPI	LOG_RSTK_CPI	LOG_MUTT_CPI
LOG_LGHT_CPI(-1)	0.779226	-0.163680	-0.062117	0.149184	0.049885	0.007403
	(0.21337)	(0.17687)	(0.17462)	(0.24470)	(0.24434)	(0.30872)
	[3.65196]	[-0.92544]	[-0.35572]	[0.60967]	[0.20417]	[0.02398]
LOG_LGHT_CPI(-2)	-0.217698	-0.061299	-0.135837	-0.411087	-0.292978	-0.157566
	(0.21240)	(0.17606)	(0.17382)	(0.24358)	(0.24322)	(0.30731)
	[-1.02497]	[-0.34818]	[-0.78148]	[-1.68770]	[-1.20459]	[-0.51274]
LOG_TRDE_CPI(-1)	0.369884	1.171658	0.479611	0.171673	0.110269	0.441420
	(0.35358)	(0.29309)	(0.28937)	(0.40549)	(0.40489)	(0.51158)
	[1.04610]	[3.99761]	[1.65746]	[0.42337]	[0.27234]	[0.86285]
LOG_TRDE_CPI(-2)	-0.524560	-0.575760	-0.655500	-0.330133	-0.468323	-0.723190
	(0.34061)	(0.28234)	(0.27875)	(0.39062)	(0.39004)	(0.49282)
	[-1.54004]	[-2.03925]	[-2.35155]	[-0.84515]	[-1.20070]	[-1.46746]
LOG_HEAV_CPI(-1)	-0.136629	0.056094	0.866540	0.191727	0.052341	-0.500122
	(0.28364)	(0.23512)	(0.23213)	(0.32529)	(0.32481)	(0.41039)
	[-0.48169]	[0.23858]	[3.73301]	[0.58941]	[0.16115]	[-1.21865]
LOG_HEAV_CPI(-2)	0.335589	0.104627	0.119496	0.019032	0.134105	0.802567
	(0.27376)	(0.22693)	(0.22404)	(0.31395)	(0.31349)	(0.39609)
	[1.22584]	[0.46106]	[0.53337]	[0.06062]	[0.42778]	[2.02621]
LOG_MERI_CPI(-1)	0.209590	0.195780	0.096325	0.865374	0.367856	0.538182
	(0.16516)	(0.13690)	(0.13516)	(0.18940)	(0.18912)	(0.23896)
	[1.26904]	[1.43008]	[0.71267]	[4.56894]	[1.94505]	[2.25221]

LOG_MERI_CPI(-2)	0.001509	0.047715	0.097644	0.172934	0.059368	-0.206844
	(0.17113)	(0.14185)	(0.14005)	(0.19625)	(0.19596)	(0.24760)
	[0.00882]	[0.33637]	[0.69721]	[0.88118]	[0.30296]	[-0.83540]
LOG_RSTK_CPI(-1)	-0.275496	-0.269392	-0.328778	-0.280724	0.393818	-0.441788
	(0.12369)	(0.10253)	(0.10123)	(0.14185)	(0.14164)	(0.17897)
	[-2.22726]	[-2.62743]	[-3.24791]	[-1.97899]	[2.78037]	[-2.46857]
LOG_RSTK_CPI(-2)	0.099273	0.106998	0.144368	0.128173	0.223420	0.253092
	(0.12564)	(0.10415)	(0.10282)	(0.14409)	(0.14387)	(0.18179)
	[0.79012]	[1.02738]	[1.40404]	[0.88955]	[1.55288]	[1.39225]
LOG_MUTT_CPI(-1)	-0.062785	-0.041596	-0.016514	-0.053176	0.038494	0.937167
	(0.08190)	(0.06789)	(0.06702)	(0.09392)	(0.09378)	(0.11850)
	[-0.76661]	[-0.61272]	[-0.24638]	[-0.56617]	[0.41045]	[7.90883]
LOG_MUTT_CPI(-2)	0.194458	0.174656	0.145517	0.183674	0.092121	-0.079110
	(0.07960)	(0.06598)	(0.06514)	(0.09128)	(0.09115)	(0.11517)
	[2.44303]	[2.64714]	[2.23387]	[2.01214]	[1.01067]	[-0.68693]
C	1.534380	1.704121	1.666306	1.297000	1.661901	0.792496
	(0.39598)	(0.32823)	(0.32406)	(0.45411)	(0.45344)	(0.57292)
	[3.87493]	[5.19185]	[5.14197]	[2.85614]	[3.66511]	[1.38326]
DD1	-0.031615	-0.020836	-0.026731	-0.019768	-0.066879	-0.012993
	(0.02957)	(0.02451)	(0.02420)	(0.03391)	(0.03386)	(0.04279)
	[-1.06908]	[-0.85001]	[-1.10454]	[-0.58289]	[-1.97497]	[-0.30367]
DD2	0.020488	0.027928	0.024339	0.058534	-0.005912	0.028480
	(0.03045)	(0.02524)	(0.02492)	(0.03492)	(0.03487)	(0.04405)
	[0.67286]	[1.10653]	[0.97676]	[1.67630]	[-0.16956]	[0.64646]
DD3	-0.010074	-0.019414	-0.030648	0.000447	-0.009401	0.055737
	(0.03082)	(0.02555)	(0.02522)	(0.03534)	(0.03529)	(0.04459)
	[-0.32687]	[-0.75998]	[-1.21515]	[0.01266]	[-0.26639]	[1.24998]
DD4	-0.064462	-0.053348	-0.059210	-0.041306	-0.069933	-0.003054
	(0.03077)	(0.02550)	(0.02518)	(0.03529)	(0.03523)	(0.04452)

	[-2.09508]	[-2.09173]	[-2.35147]	[-1.17062]	[-1.98486]	[-0.06859]
DD5	-0.053310	-0.029218	-0.019950	-0.027308	-0.061536	0.029953
	(0.03131)	(0.02595)	(0.02562)	(0.03590)	(0.03585)	(0.04530)
	[-1.70282]	[-1.12590]	[-0.77867]	[-0.76059]	[-1.71646]	[0.66125]
DD6	-0.021746	0.009233	0.009034	0.001149	-0.076789	0.079280
	(0.03162)	(0.02621)	(0.02587)	(0.03626)	(0.03620)	(0.04574)
	[-0.68781]	[0.35232]	[0.34915]	[0.03168]	[-2.12096]	[1.73310]
DD7	-0.075895	-0.056832	-0.068954	-0.061218	-0.130561	0.006383
	(0.03367)	(0.02791)	(0.02756)	(0.03862)	(0.03856)	(0.04872)
	[-2.25391]	[-2.03612]	[-2.50222]	[-1.58529]	[-3.38600]	[0.13102]
DD8	-0.128323	-0.092306	-0.092567	-0.141090	-0.128740	-0.095290
	(0.03359)	(0.02784)	(0.02749)	(0.03852)	(0.03846)	(0.04860)
	[-3.82059]	[-3.31548]	[-3.36763]	[-3.66296]	[-3.34725]	[-1.96087]
DD9	-0.089455	-0.096781	-0.087954	-0.120173	-0.063533	-0.060547
	(0.03374)	(0.02797)	(0.02761)	(0.03869)	(0.03863)	(0.04881)
	[-2.65153]	[-3.46074]	[-3.18558]	[-3.10602]	[-1.64452]	[-1.24039]
DD10	-0.145029	-0.138601	-0.133410	-0.176033	-0.096677	-0.152315
	(0.03193)	(0.02647)	(0.02613)	(0.03662)	(0.03656)	(0.04620)
	[-4.54235]	[-5.23701]	[-5.10572]	[-4.80761]	[-2.64422]	[-3.29719]
DD11	-0.024295	-0.024429	-0.019850	-0.028676	0.002604	0.031102
	(0.03188)	(0.02643)	(0.02609)	(0.03657)	(0.03651)	(0.04613)
	[-0.76195]	[-0.92431]	[-0.76070]	[-0.78423]	[0.07131]	[0.67417]
DRGHT	-0.020401	0.008284	0.001194	-0.012856	-0.010888	-0.045248
	(0.01928)	(0.01598)	(0.01578)	(0.02211)	(0.02207)	(0.02789)
	[-1.05836]	[0.51844]	[0.07567]	[-0.58158]	[-0.49325]	[-1.62240]
R-squared	0.839341	0.855157	0.866547	0.873551	0.857864	0.896599
Adj. R-squared	0.815973	0.834089	0.847136	0.855159	0.837189	0.881559
Sum sq. resids	1.081885	0.743363	0.724592	1.422868	1.418668	2.264804
S.E. equation	0.080975	0.067121	0.066268	0.092863	0.092725	0.117158
F-statistic	35.91761	40.59010	44.64129	47.49488	41.49411	59.61368

Log likelihood	221.3920	257.0432	259.4729	195.3649	195.6457	151.2076
Akaike AIC	-2.067284	-2.442560	-2.468136	-1.793314	-1.796270	-1.328501
Schwarz SC	-1.640044	-2.015320	-2.040896	-1.366074	-1.369030	-0.901261
Mean dependent	6.054296	6.187044	6.183245	5.955686	6.083092	5.561295
S.D. dependent	0.188759	0.164786	0.169493	0.244003	0.229804	0.340425

Determinant resid covariance (dof adj.)	7.12E-17
Determinant resid covariance	3.05E-17
Log likelihood	1994.993
Akaike information criterion	-19.42098
Schwarz criterion	-16.85754

Table A3.2. Full GARCH estimation outputs

Estimation Method: ARCH Maximum Likelihood (Marquardt)
Covariance specification: Diagonal BEKK
Sample: 4 192
Included observations: 189
Total system (balanced) observations 1134
Presample covariance: backcast (parameter =0.7)
Convergence achieved after 114 iterations

	Coefficient	Std. Error	z-Statistic	Prob.
C(1)	0.006157	0.005932	1.037859	0.2993
C(2)	-0.125016	0.206135	-0.606474	0.5442
C(3)	0.117092	0.267922	0.437036	0.6621
C(4)	-0.102607	0.212578	-0.482679	0.6293
C(5)	0.049855	0.139163	0.358252	0.7202
C(6)	0.005983	0.093650	0.063883	0.9491
C(7)	0.021467	0.067917	0.316086	0.7519
C(8)	0.005170	0.004920	1.050643	0.2934
C(9)	0.004282	0.004939	0.867042	0.3859
C(10)	0.007990	0.006728	1.187626	0.2350
C(11)	0.010270	0.006625	1.550188	0.1211
C(12)	0.011003	0.008403	1.309447	0.1904

Variance Equation Coefficients

C(13)	0.000350	0.000112	3.132043	0.0017
C(14)	0.000415	9.15E-05	4.539078	0.0000
C(15)	0.001049	0.000561	1.868259	0.0617
C(16)	0.000517	0.000153	3.379190	0.0007
C(17)	0.000557	0.000168	3.315929	0.0009
C(18)	0.001377	0.000498	2.764565	0.0057
C(19)	0.000512	0.000118	4.345086	0.0000
C(20)	0.001122	0.000561	2.000234	0.0455
C(21)	0.000599	0.000146	4.118024	0.0000
C(22)	0.000624	0.000152	4.111640	0.0000
C(23)	0.001214	0.000390	3.115770	0.0018
C(24)	0.001692	0.000914	1.850206	0.0643
C(25)	0.001317	0.000640	2.058065	0.0396
C(26)	0.001122	0.000467	2.400354	0.0164
C(27)	0.001573	0.000509	3.087631	0.0020
C(28)	0.000849	0.000285	2.980384	0.0029
C(29)	0.000723	0.000214	3.383061	0.0007
C(30)	0.001594	0.000537	2.968182	0.0030
C(31)	0.000958	0.000358	2.675337	0.0075
C(32)	0.001497	0.000555	2.699084	0.0070
C(33)	0.003264	0.001173	2.783168	0.0054
C(34)	0.077712	0.031933	2.433582	0.0150
C(35)	-0.041267	0.036128	-1.142247	0.2534
C(36)	-0.108911	0.053198	-2.047261	0.0406
C(37)	0.075913	0.036306	2.090957	0.0365
C(38)	0.232213	0.039558	5.870227	0.0000
C(39)	0.353108	0.060503	5.836178	0.0000
C(40)	0.960770	0.011146	86.19727	0.0000
C(41)	0.929364	0.014584	63.72454	0.0000
C(42)	0.744840	0.151613	4.912765	0.0000
C(43)	0.930401	0.021405	43.46722	0.0000
C(44)	0.893661	0.027705	32.25677	0.0000
C(45)	0.738390	0.084089	8.781095	0.0000

Log likelihood	2048.721	Schwarz criterion	-20.43156
Avg. log likelihood	1.806633	Hannan-Quinn criter.	-20.89071
Akaike info criterion	-21.20340		

Equation: E_LGHT = C(1) + C(2)*E_LGHT(-1) + C(3)*E_TRDE(-1) + C(4)*E_HEAV(-1) + C(5)*E_MERI(-1) + C(6)*E_RSTK(-1) + C(7)*E_MUTT(-1)

R-squared	-0.011160	Mean dependent var	-0.000556
Adjusted R-squared	-0.044495	S.D. dependent var	0.075469
S.E. of regression	0.077130	Sum squared resid	1.082728
Durbin-Watson stat	1.903705		

Equation: E_TRDE = C(8) + C(2)*E_LGHT(-1) + C(3)*E_TRDE(-1) + C(4)*E_HEAV(-1) + C(5)*E_MERI(-1) + C(6)*E_RSTK(-1) + C(7)*E_MUTT(-1)

R-squared	-0.010990	Mean dependent var	-0.000275
Adjusted R-squared	-0.044319	S.D. dependent var	0.062766
S.E. of regression	0.064142	Sum squared resid	0.748789
Durbin-Watson stat	1.946348		

Equation: E_HEAV = C(9) + C(2)*E_LGHT(-1) + C(3)*E_TRDE(-1) + C(4)*E_HEAV(-1) + C(5)*E_MERI(-1) + C(6)*E_RSTK(-1) + C(7)*E_MUTT(-1)

R-squared	-0.008352	Mean dependent var	-0.000272
Adjusted R-squared	-0.041595	S.D. dependent var	0.061968
S.E. of regression	0.063244	Sum squared resid	0.727966
Durbin-Watson stat	1.938114		

Equation: E_MERI = C(10) + C(2)*E_LGHT(-1) + C(3)*E_TRDE(-1) + C(4)*E_HEAV(-1) + C(5)*E_MERI(-1) + C(6)*E_RSTK(-1) + C(7)*E_MUTT(-1)

R-squared	-0.013802	Mean dependent var	-0.000680
Adjusted R-squared	-0.047224	S.D. dependent var	0.086487
S.E. of regression	0.088506	Sum squared resid	1.425653
Durbin-Watson stat	1.845282		

Equation: E_RSTK = C(11) + C(2)*E_LGHT(-1) + C(3)*E_TRDE(-1) + C(4)*E_HEAV(-1) + C(5)*E_MERI(-1) + C(6)*E_RSTK(-1) + C(7)*E_MUTT(-1)

R-squared	-0.018007	Mean dependent var	-0.000195
Adjusted R-squared	-0.051568	S.D. dependent var	0.086827

S.E. of regression	0.089037	Sum squared resid	1.442825
Durbin-Watson stat	1.926585		

Equation: E_MUTT = C(12) + C(2)*E_LGHT(-1) + C(3)*E_TRDE(-1) + C(4)*E_HEAV(-1) + C(5)*E_MERI(-1) + C(6)*E_RSTK(-1) + C(7)*E_MUTT(-1)

R-squared	-0.014361	Mean dependent var	-0.000372
Adjusted R-squared	-0.047802	S.D. dependent var	0.109637
S.E. of regression	0.112227	Sum squared resid	2.292284
Durbin-Watson stat	1.982205		

Covariance specification: Diagonal BEKK
GARCH = M + A1*RESID(-1)*RESID(-1)'*A1 + B1*GARCH(-1)*B1
M is an indefinite matrix*
A1 is a diagonal matrix
B1 is a diagonal matrix

Transformed Variance Coefficients

	Coefficient	Std. Error	z-Statistic	Prob.
M(1,1)	0.000350	0.000112	3.132043	0.0017
M(1,2)	0.000415	9.15E-05	4.539078	0.0000
M(1,3)	0.001049	0.000561	1.868259	0.0617
M(1,4)	0.000517	0.000153	3.379190	0.0007
M(1,5)	0.000557	0.000168	3.315929	0.0009
M(1,6)	0.001377	0.000498	2.764565	0.0057
M(2,2)	0.000512	0.000118	4.345086	0.0000
M(2,3)	0.001122	0.000561	2.000234	0.0455
M(2,4)	0.000599	0.000146	4.118024	0.0000
M(2,5)	0.000624	0.000152	4.111640	0.0000
M(2,6)	0.001214	0.000390	3.115770	0.0018
M(3,3)	0.001692	0.000914	1.850206	0.0643
M(3,4)	0.001317	0.000640	2.058065	0.0396
M(3,5)	0.001122	0.000467	2.400354	0.0164
M(3,6)	0.001573	0.000509	3.087631	0.0020
M(4,4)	0.000849	0.000285	2.980384	0.0029
M(4,5)	0.000723	0.000214	3.383061	0.0007

M(4,6)	0.001594	0.000537	2.968182	0.0030
M(5,5)	0.000958	0.000358	2.675337	0.0075
M(5,6)	0.001497	0.000555	2.699084	0.0070
M(6,6)	0.003264	0.001173	2.783168	0.0054
A1(1,1)	0.077712	0.031933	2.433582	0.0150
A1(2,2)	-0.041267	0.036128	-1.142247	0.2534
A1(3,3)	-0.108911	0.053198	-2.047261	0.0406
A1(4,4)	0.075913	0.036306	2.090957	0.0365
A1(5,5)	0.232213	0.039558	5.870227	0.0000
A1(6,6)	0.353108	0.060503	5.836178	0.0000
B1(1,1)	0.960770	0.011146	86.19727	0.0000
B1(2,2)	0.929364	0.014584	63.72454	0.0000
B1(3,3)	0.744840	0.151613	4.912765	0.0000
B1(4,4)	0.930401	0.021405	43.46722	0.0000
B1(5,5)	0.893661	0.027705	32.25677	0.0000
B1(6,6)	0.738390	0.084089	8.781095	0.0000

* Coefficient matrix is not PSD.