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Testing for Structural Change in Regression Models of Meat Consumption in Sweden

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Abstract

This thesis examines the meat consumption in Sweden for the last few decades. The meat industry contributes to greenhouse gas emissions causing global warming, which is one of today's most alarming issues. With a regression and time series approach, this thesis analyzes which factors have influenced the consumption of meat, with a focus on beef. Predictor variables included are consumer price index, production and price. A regression model, a price elasticity model, an autoregressive model and an error correction model will be set up to test for constant parameters and structural change.

This thesis found that price is the most influential predictor to the consumption of beef. There has been a stable development of beef consumption, constantly increasing. The consumption of beef has doubled during the last 35 years, while the price has decreased. For every one percent increase in the price of beef there is a 1.23 percent decrease in the consumption. There was evidence for structural change in the price elasticity of beef around year 2008. The structural change could be explained by an acute increase in consumption, while no distinct change in price at the same time. The results from the tests of structural change in the price elasticity model imply that it is out of the ordinary that the consumption of beef increases for some other reason than a decrease in the price of beef. Investigating meat consumption separately, there has not been structural change part from the breaks in the price elasticity. According to the results in this thesis the demand for meat had not reached a peak yet before 2014, but there is no evidence that it still has not.

Contents

1 Introduction

Global warming is one of today's most alarming issues. Lately, several newspapers and organizations have reported that the meat industry might play a major role in the greenhouse gas emissions. Swedish newspaper, Svenska Dagbladet, reports that "Beef is the biggest environmental villain" (Hedenus 2013). According to FAO[1] (2006), the livestock sector is responsible for 18 percent of the greenhouse gas emissions, which is a higher share than transport. These reports may make you wonder which factors control the meat market and if these warnings have had any impact on people's diets. In this thesis we will study the meat consumption in Sweden to try to answer the following questions;

Can we find a model to predict the consumption of beef?
Is the increase in beef consumption only an effect of lower price?
Has there been any structural change in the beef market?
Has the demand for beef reached a peak?

Similar research has been done by Ali and Pappa (2015). After analyzing structural changes in the global meat market they found indications of significant recent shifts towards white meat, due to increasing environmental and health concerns among consumers in developed countries. Although, developing markets still focus on red meat. A report from the Swedish Board of Agriculture[2] (Lööv and Widell 2009) explains that meat is the most price sensitive type of consumer good and the only food group with a price elasticity greater than 1. This means that the percentage change in quantity demanded is greater than the percentage change in price. Note that only Swedish data from 1960-2006 was examined.

To answer previous questions we will analyze data from the statistical database of the Swedish Board of Agriculture[3] and Statistics Sweden[4]. We will study the consumption of meat, the price of meat and the production of meat, with a focus on beef. Data on poultry will be applied to models in Section 3.1. The consumer price index will also play a role. Following is a presentation of the most important data used in this study.

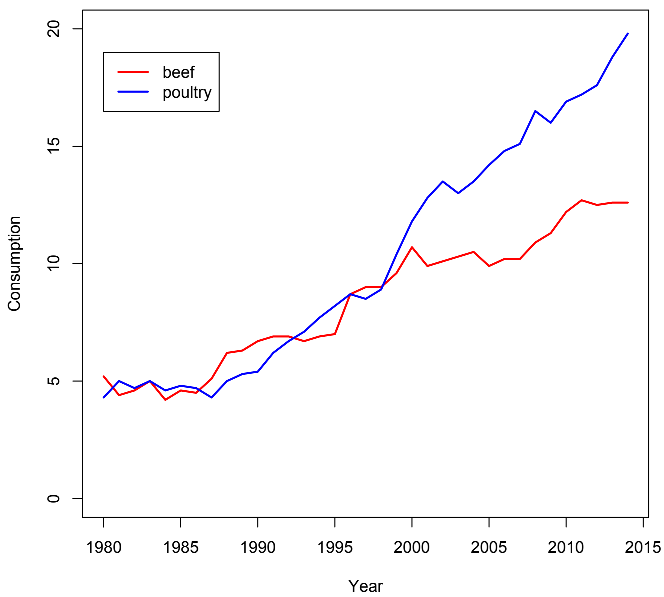

Figure 1: Direct consumption in kg per person and year (2014 is preliminary)

[1]Food and Agriculture Organization of the United Nations
[2]Jordbruksverket
[3]Jordbruksverkets statistikdatabas
[4]Statistiska centralbyrån, SCB

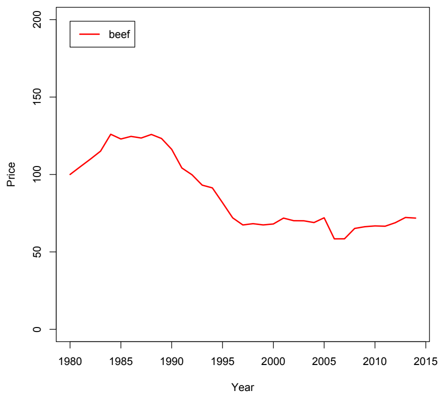

Figure 2: Price index with base year 1980 (adjusted for inflation)

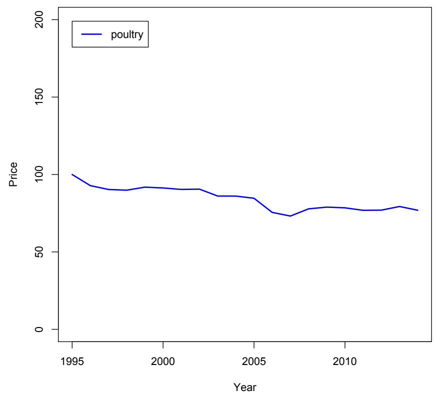

Figure 3: Price index with base year 1995 (adjusted for inflation)

The consumption of both beef and poultry has clearly increased (Figure 1) while the price of beef and poultry has decreased, but in a less drastic way (Figure 2 and Figure 3). Although, there was an increase in the price of beef 1980-1985, before the price began to decrease. Note that there are no data on poultry price during these years.

The price data used in this thesis is indexed, for more information and an explanation of the inflation adjustment, see Section 2.1. An explanation of consumer price index, CPI, can also be found in Section 2.1. The meat consumption data is the direct consumption of meat, i.e., the total deliveries of meat from producers to private households, restaurants, catering facilities, non-domestic kitchens and the producers own household use. The production of meat is measured in 1000 tonnes. All data used in this thesis can be found in Appendix.

To examine these questions, we will set up a regression model, a price elasticity model, an autoregressive model and an error correction model to predict the consumption of beef and to analyze the effect of change in price. We will then test for structural change in the last three models by generalized fluctuation tests, such as OLS-CUSUM and Rec-CUSUM, and also with F-tests.

2 Theory

2.1 Basic Concepts in Time Series and Econometrics

There are a few basic concepts in econometrics that are needed in some models and methods of this thesis. When analyzing series of data it might help to look at a series of indexes instead. Every index is compared to a base value that usually equals 100 and every *index* will be of form

$$index_i = \frac{value_i}{value_{base}}$$

where i is the current time, often in years (Körner and Wahlgren 2012).

Consumer price index (CPI) is an average measure of the price level for all private consumption in Sweden. When comparing prices from different times, you might need to adjust it for the current price level. In this thesis, the *inflation-adjusted price* at time i will refer to

$$inflation\text{-}adjusted\ price_i = \frac{price_i}{CPI_i}$$

(Körner and Wahlgren 2012).

2.2 Regression

2.2.1 Simple Linear Regression

Simple linear regression is a common statistical method used to relate one variable to another explanatory variable. The response variable y and the regressor x make up the *simple linear regression model*

$$y_i = \beta_0 + \beta_1 x_i + e_i$$

consisting of the mean function and the variance function

$$\mathsf{E}[Y|X = x] = \beta_0 + \beta_1 x$$
$$\mathsf{V}[Y|X = x] = \sigma^2$$

The parameter β_0 in the mean function is the intercept, and β_1 is the slope. In the simple linear regression model the variance $\sigma^2 > 0$ is assumed to be constant. The statistical error term e accounts for any differences between the observed data and expected value (Weisberg 2013).

2.2.2 Multiple Linear Regression

By generalizing the simple linear regression model with additional regressors we get the *multiple linear regression model* with mean function

$$\mathsf{E}[Y|X = x] = \beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p$$

The β parameters are unknown, as in simple regression, and when $p = 1$ we get the simple linear regression model. Another way to express multiple linear regression is in matrix form

$$\boldsymbol{Y} = \boldsymbol{X\beta} + \boldsymbol{e}$$

with

$$\boldsymbol{Y} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix}, \ \boldsymbol{X} = \begin{pmatrix} 1 & x_{11} & \cdots & x_{1p} \\ 1 & x_{21} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & \cdots & x_{np} \end{pmatrix}, \ \boldsymbol{\beta} = \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{pmatrix}, \ \boldsymbol{e} = \begin{pmatrix} e_1 \\ e_2 \\ \vdots \\ e_n \end{pmatrix}$$

When finding a multiple regression model you may start with a potential set of predictors. From this set of predictors we create a set of regressors that may consist of the intercept, some of the predictors, transformations or combinations of the predictors, dummy variables and other components (Weisberg 2013).

2.3 Price Elasticity Model

To understand the effect on sales by change in price of a product one may look at the *price elasticity.* A simple linear model of price elasticity may be

$$Q = \beta_0 + \beta_1 P$$

where P = Price and Q = Quantity. By adding a statistical error term we get a simple linear regression model.

We are particularly interested in the percentage change in consumption of a one-percentage change in price. In this case we may use logarithms to estimate percentage effects with a simple linear regression model

$$\log(Q) = \beta_0 + \beta_1 \log(P) + e$$

where log refers to the natural logarithm. Following Sheather (2009) we find that

$$\begin{aligned}
\beta_1 &= \frac{\Delta \log(Q)}{\Delta \log(P)} \\
&= \frac{\log(Q_i) - \log(Q_{i-1})}{\log(P_i) - \log(P_{i-1})} \\
&= \frac{\log(Q_i/Q_{i-1})}{\log(P_i/P_{i-1})} \\
&\cong \frac{Q_i/Q_{i-1} - 1}{P_i/P_{i-1} - 1} \text{ (using } \log(1+z) \cong z \text{ and assuming } \beta_1 \text{ is small)} \\
&= \frac{\%\Delta Q}{\%\Delta P}
\end{aligned} \tag{2.1}$$

By rewriting (2.1) we can see that for every one percent increase in P the model predicts a β_1 percent increase in Q

$$\%\Delta Q = \beta_1 \%\Delta P$$

2.4 Time Series and Differencing

A *time series* $\{x_t\}$ is a sequence of data indexed in time order. A stationary time series is a time series whose statistical properties are constant over time, such that there are no trends or seasonal periodicity. Many time series are non-stationary because of seasonal effects or trends. Stationarizing a time series through differencing can be a way to remove trends, whether these trends are stochastic or deterministic.

When differencing a time series you get an integrated time series. A series $\{x_t\}$ is integrated of order d if you get white noise $\{w_t\}$ after differencing $\{x_t\}$ d times (Cowpertwait and Metcalfe 2009).

When taking first-order differences of the beef consumption and beef price the increasing and decreasing trends seen in the introduction (Figure 1 and Figure 2) are no longer apparent, as seen in the plots of the differenced series (Figure 4 and Figure 5).

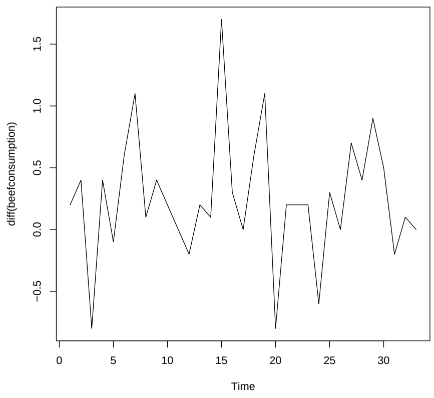

Figure 4: Error correction model: diffconsumption

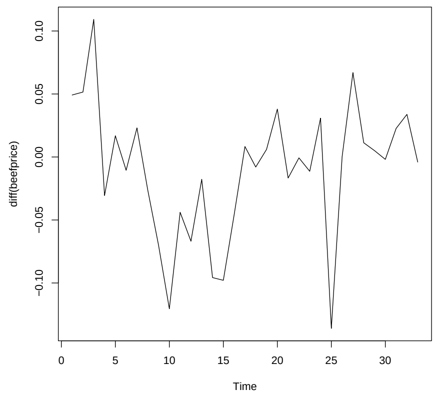

Figure 5: Error correction model: diffprice

2.5 Autoregressive Model

Autoregressive processes are models for stationary time series. An *autoregressive process* $\{y_t\}$ of order p satisfies the equation

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \ldots + \phi_p y_{t-p} + e_t$$

where e_t is an "innovation" term that incorporates everything new in the series at time t. Note that the current value of y_t is a linear combination of the last p values of itself. In this thesis, we will do some statistical tests on the first-order autoregressive model, AR(1)

$$y_t = \phi y_{t-1} + e_t \tag{2.2}$$

(e.g. Cryer and Chan 2008).

2.6 Error Correction Model

Now, consider two time series $\{x_t\}$ and $\{y_t\}$. Applied time series regressions may take the form of an *error correction model*. Error correction models can be used when there is a stochastic trend, when y_{t1} and y_{t2} are cointegrated. One way to express the error correction model for a simple regression model is

$$\Delta y_t = \beta_1 + \beta_2 u_{t-1} + \beta_3 \Delta x_t + e_t \tag{2.3}$$

$$u_t = y_t - \alpha_1 - \alpha_2 x_t \tag{2.4}$$

based on Hansen (1992).

We estimate the cointegration equation (2.4) by ordinary least squares and use the residuals $\hat{u}_t$ as regressors in the first equation (2.3). Thus, the response variable is the change in y_t and the regressors are the change in x_t and the cointegration residuals (Zeileis et al. 2002).

3 Models and Methods

3.1 Regression Model

Let us begin with a regression model with the response variable representing the beef consumption in Sweden through the years 1995-2014. In this first model we use the following predictors; consumer price index (CPI), beef production, beef price, poultry price, inflation-adjusted beef price and inflation-adjusted poultry price.

$$\begin{aligned} \text{beef consumption} \sim \text{CPI} + \text{beef production} + \text{beef price} + \text{poultry price} + \\ \text{inflation-adjusted beef price} + \text{inflation-adjusted poultry price} \end{aligned} \tag{3.1}$$

These predictors are chosen because they are descriptive of the meat market. The poultry price is included in the model to see if price change in substitutes may change the demand for the product we are interested in. The inflation-adjusted prices are also included in the model even though there might be some collinearity between the actual prices and the adjusted prices. The inflation-adjusted prices might be more descriptive of the actual cost. A comparison of models with different combinations of price predictors can be done.

We want to predict how much of an impact these predictors have on the beef consumption and which ones of these predictors that has the most significance to the model. To improve the model we will stepwise remove the least significant regressors, one-by-one, until we reach a model where all regressors have a p-value lower than $\alpha = 0.05$.

3.2 Price Elasticity Model

When setting up the price elasticity model from Section 2.3

$$\log(Q) = \beta_0 + \beta_1 \log(P) + e$$

we use Q = beef consumption and P = inflation-adjusted beef price, through the years 1980-2014.

3.3 Testing for Structural Change

3.3.1 Models and hypothesis

Consider the linear regression model

$$\left.\begin{aligned} y_t &= x_t^T \beta_t + e_t \\ e_t &\sim N(0, \sigma^2) \end{aligned}\right\} t = 1, \ldots, T$$

where $x_t = (1, x_{2t}, \ldots, x_{kt})^T$ and $\beta_t = (\beta_{1t}, \beta_{2t}, \ldots, \beta_{kt})^T$. We want x_t and e_t to be weakly dependent, meaning there are no deterministic or stochastic trends (Hansen 1992). Note that β_t is written with the subscript t to indicate that it may vary with time. When testing for structural change, we want to test whether the regression coefficients vary over time or if $\beta_t = \beta_0$, a constant, for all $t = 1, \ldots, T$. We set up the hypothesis for constant parameters over time

$$\begin{aligned} &H_0 : \beta_t = \beta_0 \text{ for all } t = 1, \ldots, T \\ &H_1 : \beta_t \neq \beta_0 \text{ for at least one } t \in [1, \ldots, T] \end{aligned}$$

(Westlund and Törnkvist 1989). We assume that $||x_i|| = O(1)$ and that for some finite regular matrix Q,

$$\frac{1}{T} \sum_{i=1}^{T} x_i x_i^T \to Q$$

(Zeileis et al. 2002).

We will apply the regression model for $k = 2$, representing the price elasticity model

$$y_t = \beta_{1t} + \beta_{2t}x_{2t} + e_t$$

with regression coefficients β, beef consumption y_t and beef price x_{2t}.

We may also test for structural change in an error correction model and in an autoregressive model. In this case, we will use the error correction model

$$\begin{aligned}\Delta c_t &= \beta_1 + \beta_2 u_{t-1} + \beta_3 \Delta p_t + e_t \\ u_t &= c_t - \alpha_1 - \alpha_2 p_t\end{aligned}$$

where c_t is beef consumption, u_t are the cointegrated residuals and p_t is beef price. A simpler expression of our error correction model without parameters or error term is

$$\Delta\text{consumption} \sim \text{cointegrated residuals} + \Delta\text{price}$$

We will also test on the first-order autoregressive model from equation (2.2)

$$Y_t = \phi Y_{t-1} + e_t$$

where Y_t is beef consumption at time t and Y_{t-1} is beef consumption at time $t-1$. In these cases we will have annual data through 1980-2014.

3.3.2 Generalized Fluctuation Tests

When analyzing parameter variabilities, we may study the recursive residuals

$$w_t = \frac{y_t - x_t^T b_{t-1}}{\sqrt{1 + x_t^T (X_{t-1}^T X_{t-1})^{-1} x_t}}, \; t = k+1, \ldots, T$$

where $X_{t-1}^T = (x_1, \ldots, x_{t-1})$, $b_{t-1} = (X_{t-1}^T X_{t-1})^{-1} X_{t-1}^T Y_{t-1}$ and $Y_{t-1}^T = (y_1, \ldots, y_{t-1})$. In other words, b_{t-1} is the least-squares estimate of β based on the first $t-1$ observations, assuming H_0 is true. In this case $w_t \sim N(0, \sigma^2)$ under the null hypothesis. Also, assuming H_0 is true, $w_{k+1}, \ldots, w_T$ are independent (Brown et al. 1975). The corresponding variance estimate is

$$\hat{\sigma}_w^2 = \frac{1}{T-k} \sum_{t=k+1}^{T} (w_t - \bar{w})^2$$

The ordinary least squares estimate of the residuals is

$$\hat{e}_t = y_t - x_t^T \hat{\beta}$$

with variance estimate

$$\hat{\sigma}_e^2 = \frac{1}{T-k} \sum_{t=1}^{T} \hat{e}_t^2$$

(Zeileis et al. 2002).

The generalized fluctuation tests fit a model on given data to derive an empirical process that describes fluctuation in either the residuals or in the estimates. If the empirical process path crosses the boundaries, calculated from the limiting processes, the null hypothesis of no fluctuation should be rejected at the current significance level (Zeileis et al. 2002).

Cusum processes consist of cumulated sums of standardized residuals. We consider cumulated sums of recursive residuals

$$W_T(t) = \frac{1}{\hat{\sigma}_w \sqrt{T-k}} \sum_{i=k+1}^{k+\lfloor t(T-k) \rfloor} w_i \qquad (0 \leq t \leq 1)$$

(Brown et al. 1975). Under the null hypothesis the limiting process for $W_T(t)$ is the Standard Brownian Motion $W(t)$, and the central limit theorem holds. This means that $W_T \implies W$, as $T \to \infty$, where " $\implies$ " denotes weak convergence. If structural change occurs at t_0, the recursive residuals will only have zero mean up to that point and the path of the process will leave its mean afterwards.

The empirical fluctuation process of cumulated sums of ordinary least squares residuals can be expressed as

$$W_T^0(t) = \frac{1}{\hat{\sigma}_e \sqrt{T}} \sum_{i=k+1}^{\lfloor tT \rfloor} \hat{e}_i \qquad (0 \leq t \leq 1)$$

Under the null hypothesis the limiting process for $W_T^0(t)$ is the Standard Brownian Bridge $W^0(t) = W(t) - tW(1)$. The path of the process starts and ends at 0, and for any point of structural change the path will have a strong peak (Zeileis et al. 2002).

From this point and forward, we will refer to the cumulated sums of recursive residuals as Rec-CUSUM and the cumulated sums of ordinary least squares residuals as OLS-CUSUM. When doing generalized fluctuation tests on Rec-CUSUM and OLS-CUSUM processes, the null hypothesis of no structural change should be rejected when the fluctuation of the empirical process gets large compared to the fluctuation of the limiting process. We may compare to some appropriate boundary $b(t)$ that the empirical process will only cross for a given probability α. Thus, if the process exceeds $[-b(t), b(t)]$ for any t, we reject the null hypothesis at confidence level α. The commonly used boundaries are the *linear* boundaries

$$\begin{aligned} b(t) &= \lambda(1 + 2t) \\ b(t) &= \lambda \end{aligned} \tag{3.2}$$

respectively, for the Rec-Cusum and the OLS-CUSUM, with λ as confidence level. These are chosen because they are a simplified version of the more proportional *non-linear* boundaries

$$\begin{aligned} b(t) &= \lambda\sqrt{t} \\ b(t) &= \lambda\sqrt{t(1-t)} \end{aligned} \tag{3.3}$$

The limiting processes are non-stationary and these boundary functions (3.3) are proportional to the standard deviation functions of the limiting processes, but the linear boundaries (3.2) are more commonly used (Zeileis et al. 2002).

We may plot the empirical fluctuation processes with its boundaries to visualize information about structural changes. To carry out a test of significance we turn to the test statistics S for the Rec-CUSUM and the OLS-CUSUM

$$S = \max_t \frac{efp(t)}{f(t)}$$

where $efp(t)$ is the empirical fluctuation process and $f(t)$ depends on the boundary such that $b(t) = \lambda f(t)$. We want $|S| < |b(t)|$ for all t for the null hypothesis to hold (Zeileis et al. 2002).

3.3.3 F-tests

When testing the null hypothesis of no structural change with F test statistics the alternative hypothesis must be specified. The F tests are designed to test against a single shift alternative that can be formulated as

$$\beta_i = \begin{cases} \beta_A \ (1 \leq i \leq i_0) \\ \beta_B \ (i_0 < i \leq T) \end{cases}$$

where i_0 is a point of change in the interval $(k, T-k)$. When a potential point of change i_0 is known, we reject the null hypothesis whenever

$$F_{i_0} = \frac{\hat{e}^T\hat{e} - \hat{u}^T\hat{u}}{(\hat{u}^T\hat{u})/(T-2k)}$$

is too large, where $\hat{u} = (\hat{e}_A, \hat{e}_B)^T$ are the residuals from the full model and $\hat{e}$ are the residuals from the restricted model. The residuals in the full model are estimated separately, while the residuals in the restricted model are estimated for all observations at once. The test statistic F_{i0} has an asymptotic χ^2 distribution with k degrees of freedom. Assuming normality, F_{i0}/k has an F distribution with k and $T - 2k$ degrees of freedom (Zeileis et al. 2002).

To extend this from one potential point of change i_0 to a set of potential points of change in the interval $[\underline{i}, \bar{i}]$, we calculate the F statistics F_i for $k < \underline{i} \leq i \leq \bar{i} < T - k$ and reject the null hypothesis if F_i gets too large for any i. Under the null hypothesis of no structural change, boundaries can be computed such that the asymptotic probability that the supremum (or the mean) of the statistics F_i (for $\underline{i} \leq i \leq \bar{i}$) exceeds this boundary is α. As for the empirical fluctuation tests, the null hypothesis is rejected if the path of the process crosses the lines of the boundary. When testing the significance, there are three different test statistics with following asymptotic distribution

$$supF = \sup_{\underline{i} \leq i \leq \bar{i}} F_i$$

$$aveF = \frac{1}{\bar{i} - \underline{i} + 1} \sum_{i=\underline{i}}^{\bar{i}} F_i$$

$$expF = \log\left(\frac{1}{\bar{i} - \underline{i} + 1} \sum_{i=\underline{i}}^{\bar{i}} \exp(0.5 F_i)\right)$$

The *supF* and the *aveF* are described above, the *expF* is similarly to be rejected when the F statistics gets too large (Zeileis et al. 2002). The p-values are computed based on Hansen (1997).

4 Results

4.1 Regression

When setting up our first model according to equation (3.1) we get the following result

Listing 1: R

```
Call:
lm(formula = beefconsumption ~ CPI + beefproduction + beefprice +
    poultryprice + inflationbeefprice + inflationpoultryprice)

Residuals:
     Min       1Q   Median      3Q     Max
-0.65710 -0.20653 -0.03942 0.19164 0.72859

 Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)              50.17310   28.68218   1.749 0.103796
CPI                      -0.17944    0.10034  -1.788 0.097044 .
beefproduction            0.04570    0.02543   1.797 0.095514 .
beefprice                 1.04853    0.25640   4.089 0.001278 **
poultryprice             -0.19514    0.31671  -0.616 0.548438
 inflationbeefprice    -315.74628   70.17710  -4.499 0.000598 ***
 inflationpoultryprice   88.71998   85.40920   1.039 0.317850
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3962 on 13 degrees of freedom
Multiple R-squared: 0.9529,     Adjusted R-squared: 0.9311
F-statistic:  43.8 on 6 and 13 DF, p-value: 6.98e-08
```

This model contains several insignificant regressors. By removing the least significant regressors one by one until we reach a model where all regressors have a p-value below $\alpha = 0.05$ we find our desired set of regressors.

Listing 2: R

```
Call:
lm(formula = beefconsumption ~ CPI + beefprice + inflationbeefprice +
     inflationpoultryprice )

Residuals:
     Min       1Q   Median      3Q     Max
-0.52442 -0.20853 -0.04179 0.13892 0.89544

 Coefficients:
                         Estimate Std. Error t value Pr(>|t|)
(Intercept)              62.46937   24.61861   2.537 0.022755 *
CPI                      -0.21068    0.08432  -2.499 0.024570 *
beefprice                 0.97579    0.23551   4.143 0.000867 ***
 inflationbeefprice    -306.34538   64.32320  -4.763 0.000252 ***
 inflationpoultryprice   53.61460   17.97487   2.983 0.009293 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4123 on 15 degrees of freedom
Multiple R-squared: 0.9411,     Adjusted R-squared: 0.9254
F-statistic:  59.9 on 4 and 15 DF, p-value: 4.82e-09
```

This final model has a significant set of regressors and a high R^2-value. The price of poultry and the beef production are no longer part of the model and the price of beef and the inflation-adjusted price of beef has the lowest p-values. Very similar results were obtained by other models (see Appendix). These other models that were studied had only beef price and poultry price or only inflation-adjusted beef price and inflation-adjusted poultry price as the start set of predictors, instead of all four together. All models have in common that the predictor for beef production is removed.

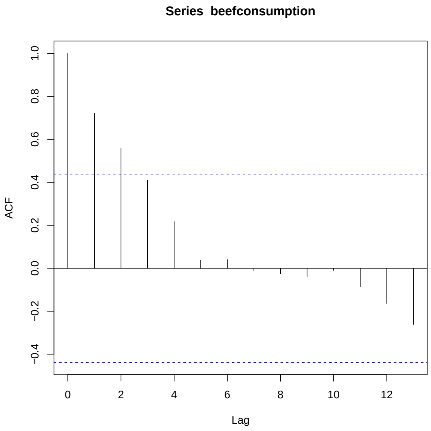

Figure 6: ACF of beef consumption

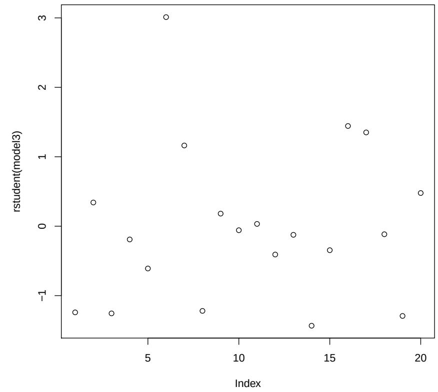

Figure 7: Rstudent of final model

The ACF plot of beef consumption shows a clear trend (Figure 6). In the rstudent plot (Figure 7) there appeared to be an outlier. When removing the outlier (year 2000) from the original data we reached a significant model very similar to the one before, see Appendix for comparison. This outlier seems to have had little impact even though it is the second most influential point, according to Cook's distance (Figure 8).

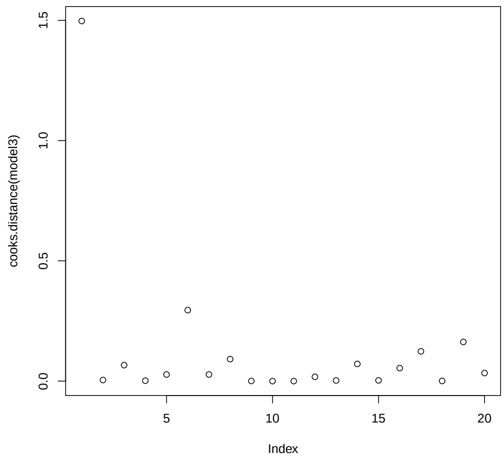

Figure 8: Cooks distance of final model

4.2 Price Elasticity

When setting up the price elasticity model

$$\log(Q) = \beta_0 + \beta_1 \log(P) + e \tag{4.1}$$

where Q = beef consumption and P = inflation-adjusted beef price we get a high R^2-value and high significance on both the intercept and the inflation-adjusted price of beef.

Listing 3: R

```
Call:
lm(formula = log(beefconsumption) ~ log(beefprice))

Residuals:
     Min       1Q   Median       3Q      Max
-0.31765 -0.11780 0.01575  0.09629  0.27294

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)     1.85940    0.03234   57.49  < 2e-16 ***
log(beefprice) -1.23392    0.10486  -11.77 2.37e-13 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1595 on 33 degrees of freedom
Multiple R-squared: 0.8075,     Adjusted R-squared: 0.8017
F-statistic: 138.5 on 1 and 33 DF, p-value: 2.37e-13
```

The same problems with time dependence occurs even in the simple model of price elasticity. The rstudent plot (Figure 9), normal QQ-plot (Figure 10) and histogram of rstudent (see all plots in Appendix) are similar to the ones from the regression model.

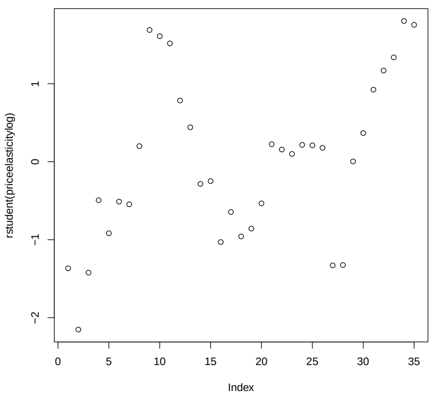

Figure 9: Rstudent of price elasticity model

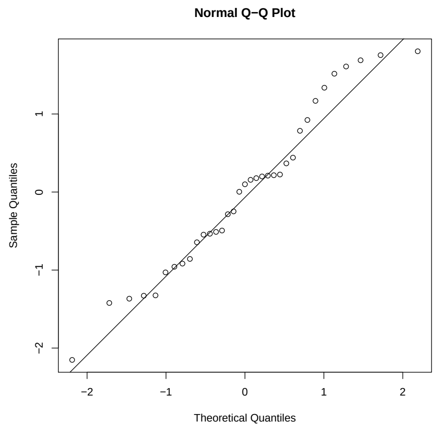

Figure 10: Normal QQ-plot of price elasticity model

4.3 Testing for Structural Change

The default significance level used in the following tests is $\alpha = 0.05$. The $\underline{i}$ and $\bar{i}$ used in the F-tests are 0.15 and 0.85 respectively, as fractions of the sample.

4.3.1 Price Elasticity Model

The test results for the Rec-CUSUM and OLS-CUSUM in the price elasticity model (without log-transformation) are

Table 1:

OLS-based CUSUM test	**Recursive CUSUM test**
S0 = 1.5166	S = 2.4233
p-value = 0.0201	p-value = 1.253e-10

with boundary $b(t) = 1.3581$ for the OLS-CUSUM test (see Figure 11). For the Rec-CUSUM test, the boundary is visualized in the plot below (Figure 12). For more exact numbers, see

Appendix.

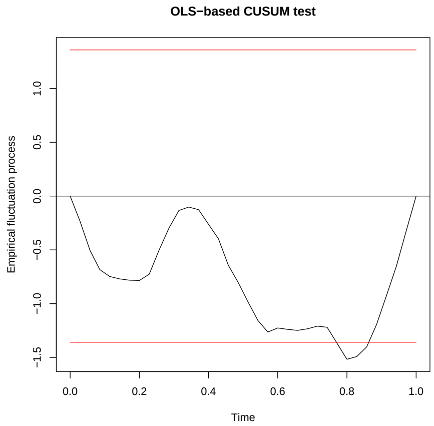

Figure 11: OLS-CUSUM

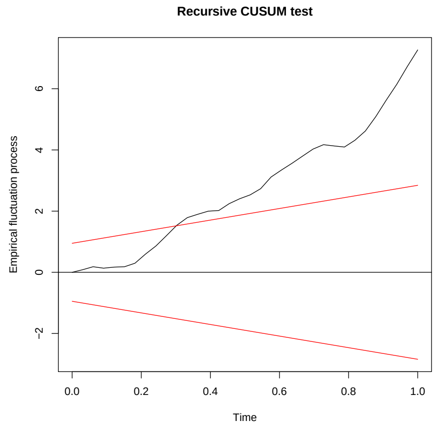

Figure 12: Rec-CUSUM

The results of the F-tests are

Table 2:

expF test	**supF test**	**aveF test**
exp.F = 19.0956	sup.F = 42.2122	ave.F = 20.1625
p-value = 1.075e-05	p-value = 2.715e-08	p-value = 5.406e-05

with boundary $b(t) = 11.64361$, see plot below (Figure 13).

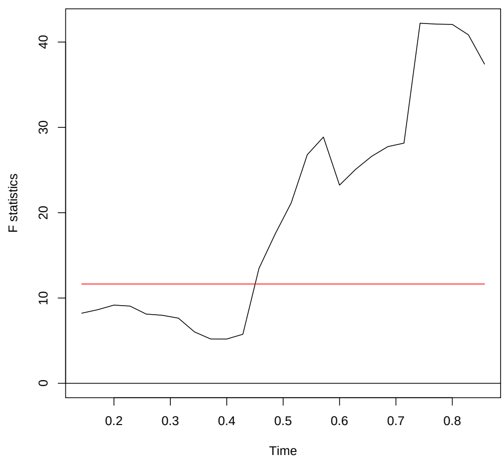

Figure 13: supF

4.3.2 Autoregressive Model

The test results for the Rec-CUSUM and OLS-CUSUM in the AR(1) model are

Table 3:

OLS-based CUSUM test	**Recursive CUSUM test**
S0 = 0.6598	S = 0.7356
p-value = 0.7767	p-value = 0.2039

with boundary $b(t) = 1.3581$ for the OLS-CUSUM test (see Figure 14). For the Rec-CUSUM test, the boundary is visualized in the plot below (Figure 15). For more exact numbers, see Appendix.

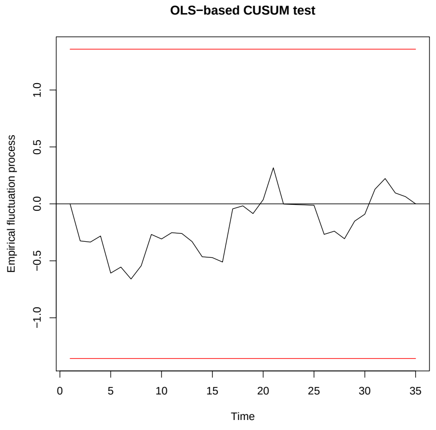

Figure 14: OLS-CUSUM

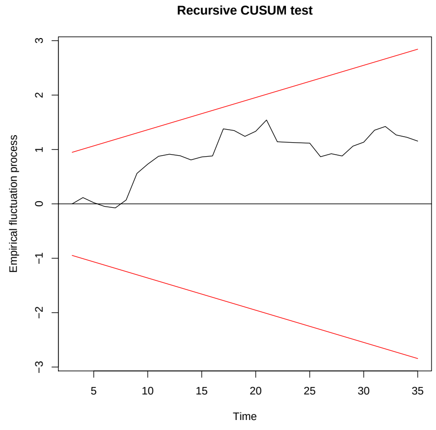

Figure 15: Rec-CUSUM

The results of the F-tests are

Table 4:

expF test	**supF test**	**aveF test**
exp.F $= 3.3563$	sup.F $= 11.6532$	ave.F $= 2.6206$
p-value $= 0.04261$	p-value $= 0.04879$	p-value $= 0.2382$

with boundary $b(t) = 11.59453$, see plot below (Figure 16).

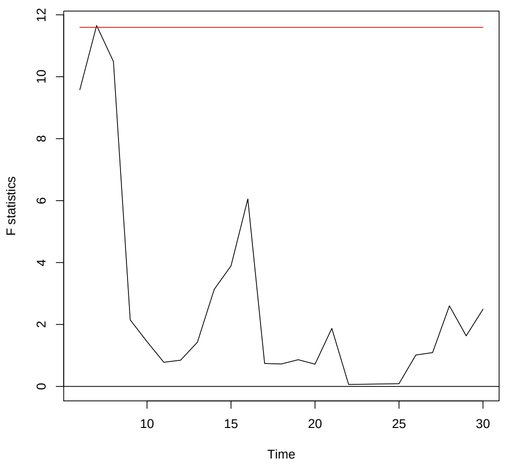

Figure 16: supF

4.3.3 Error Correction Model

The test results for the Rec-CUSUM and OLS-CUSUM in the error correction model are

Table 5:

OLS-based CUSUM test	**Recursive CUSUM test**
S0 = 0.7099	S = 0.4827
p-value = 0.6947	p-value = 0.6661

with boundary $b(t) = 1.3581$ for the OLS-CUSUM test (see Figure 17). For the Rec-CUSUM test, the boundary is visualized in the plot below (Figure 18). For more exact numbers, see Appendix.

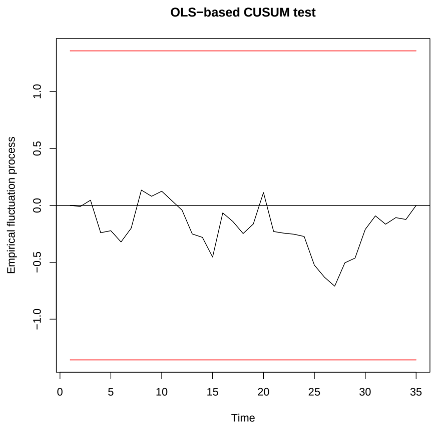

Figure 17: OLS-CUSUM

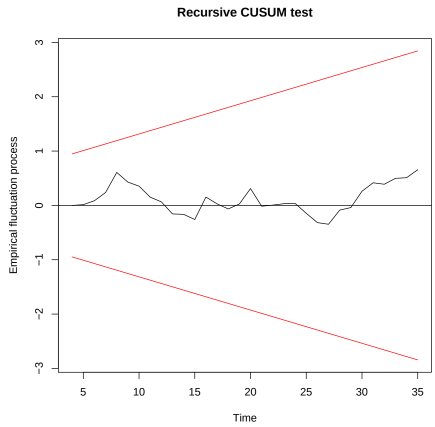

Figure 18: Rec-CUSUM

The results of the F-tests are

Table 6:

expF test	**supF test**	**aveF test**
exp.F = 1.3429	sup.F = 5.2935	ave.F = 2.0732
p-value = 0.6538	p-value = 0.7656	p-value = 0.6702

with boundary $b(t) = 13.91$, see plot below (Figure 19).

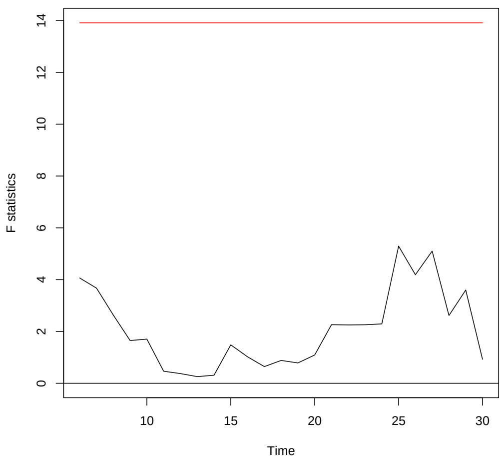

Figure 19: supF

5 Discussion

The first regression model (Listing 1) contains several insignificant regressors. By removing the least significant regressors one by one until we reach a model where all regressors have a p-value below $\alpha = 0.05$ we find our desired set of regressors, as in our final regression model (Listing 2). The final model has a significant set of regressors and a high R^2-value which might imply that this set of regressors make a good model for the beef consumption. The price of poultry and the beef production are no longer part of the model and it seems like the price of beef and the inflation-adjusted price of beef are the most influential regressors. When looking further into the data we can see that a regression approach to this problem might not be optimal. The rstudent plot (Figure 7) shows a slight pattern that might imply an inadequate model. The ACF plot (Figure 6) is strong evidence that this data is not very fit for a regression model.

In the rstudent plot there appeared to be an outlier. When removing the outlier (year 2000) from the original data we reached a significant model very similar to the previous regression model, see Appendix for comparison. This outlier seems to have had little impact even though it was the second most influential point, according to Cook's distance (Figure 8). In the rstudent plot (Figure 7) there are only two points outside the $[-2, 2]$ band, which is an acceptable amount.

When setting up the price elasticity model we get a high R^2-value and high significance on both the intercept and the inflation-adjusted price of beef. The same problems with time dependence occurs even in the simple model of price elasticity. The rstudent plot (Figure 9) shows an even stronger pattern this time. Disregarding the inadequateness, with $\beta_1 \approx -1.23$ this model implies that for every one percent increase in the price of beef there is a 1.23 percent decrease in the consumption, which seems very likely.

When looking at the CUSUM tests of the price elasticity model (without log-transformation), we find that there is a point of change around $t = 0.8$, which translates to year 2008. Both the OLS-CUSUM test and the Rec-CUSUM test exceeds the boundary with quite low p-value. In the OLS-CUSUM plot (Figure 11) it happens around year 2008. In the Rec-CUSUM plot (Figure 12) it happens already at $t = 0.3$, which translates to year 1990, but there is a clear peak around year 2008. The F-tests also imply that we should reject the null hypothesis of no structural change and the F statistics plot (Figure 13) indicates a break in the late 1990s, but $supF = 42.2122$ happens around 2008. The structural change around 2008 could possibly be explained by an acute increase in consumption, while the price stayed about the same at this time. This differs from the ordinary, since the increase in consumption usually is an effect of a lowering of the price.

The test results for the Rec-CUSUM and OLS-CUSUM in the AR(1)-model are not as intriguing. Both tests imply that we should not reject the null hypothesis of no structural change and the plots (Figure 14 and 15) shows that the process path is far from the boundary at all times. The F-tests have similar results, although the supF slightly exceeds the boundary (Table 4). When looking at the plot (Figure 16), the peak appears to be very small. Considering the previous results on the AR(1)-model, we may draw the conclusion that there is no structural change in this model. This can be interpreted as a stable development of the beef consumption, constantly increasing.

In our last model to test for structural change, the error correction model, we find similar results as for the AR(1)-model. The OLS-based CUSUM test and the Recursive CUSUM test both imply that the null hypothesis is not to be rejected. The plots of both tests (Figure 17 and 18) show process paths inside the boundaries. The F-tests give the same result of no structural change in the error correction model. All three F test statistics are far below the boundary as seen in the result summary (Table 6), and also in the F statistics plot (Figure 19).

We have a high p-value for the AR(1)-model in the OLS-CUSUM test, Rec-CUSUM test and aveF test. The same goes for the error correction model in the OLS-CUSUM test, Rec-CUSUM test, supF test, expF test and aveF test. We can draw the conclusion that the tests that were close to significant had poor power. To mention an example, the AR(1)-model had a small peak as shown in the F statistics plot (Figure 16). The high value for $p = 0.04879$ (right below

$\alpha = 0.05$) indicates that this small implication of significance can be rejected.

To answer the questions formulated in the beginning of this thesis, regression models did not seem to be the best way to predict the consumption of meat, because of its time dependency. The development of the meat consumption does not seem to be strictly controlled by the price, even though it is the main factor. Although in general, the price has decreased while our consumption has increased. Thus, our main conclusion is that the results from the tests of structural change in the price elasticity model imply that it is out of the ordinary that the consumption of beef increases for some other reason than a decrease in the price of beef. In the meat consumption alone there has not been structural change, part from the breaks in the price elasticity. According to the results in this thesis the demand for meat had not reached a peak yet before 2014, but there is no evidence that it still has not.

Acknowledgements

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Appendix

Data

All meat data is collected from Jordbruksverkets statistikdatabas. The consumer price index data is collected from Statistiska centralbyrån.

Direct consumption in kg per person and year 1980-2014 (2014 is preliminary)

```
> beefconsumption
5.2  4.4  4.6  5.0  4.2  4.6  4.5  5.1  6.2  6.3  6.7  6.9  6.9  6.7  6.9  7.0  8.7  9.0  9.0  9.6 10.7  9.9
    10.1 10.3 10.5  9.9 10.2 10.2 10.9 11.3 12.2 12.7 12.5 12.6 12.6
> poultryconsumption
4.3  5.0  4.7  5.0  4.6  4.8  4.7  4.3  5.0  5.3  5.4  6.2  6.7  7.1  7.7  8.2  8.7  8.5  8.9 10.4 11.8 12.8
    13.5 13.0 13.5 14.2 14.8 15.1 16.5 16.0 16.9 17.2 17.6 18.8 19.8
```

Price index 1980-2014

```
> beefprice
100.00000 104.99554 109.91539 115.06829 125.98645 122.92683 124.61001 123.55513 125.86304 123.24543
    116.24434 104.19724 99.80678 93.12395 91.34935  81.77736 71.98893 67.39602  68.22497  67.42696
    68.02623  71.82724  70.15488 70.08476  68.94904  72.02811 58.42053  58.44878  65.14250  66.27093
    66.77489  66.58534 68.85244  72.23372  71.83031
```

Price index 1995-2014

```
> poultryprice
100.00000  93.30000  91.40000  90.70000  93.10000  93.40000  94.66090  96.89316  93.90436 94.21258  93.10112
    84.17272  83.36274  91.71391  92.56113  93.10112 93.87386  94.87004 97.71894  94.57212
```

Production 1995-2014

```
> beefproduction
143.33 137.42 148.89 142.50 144.04 149.81 143.19 146.48 140.40 142.42 135.94 137.41 133.54 128.79 139.83
    137.80 137.88 125.34 125.88 131.62
```

Consumer Price Index 1980-2014

```
> CPI
100.00 112.10 121.73 132.53 143.19 153.75 160.26 166.97 176.70 188.08 207.58 227.18 232.58 243.57 248.83
    254.94 256.30 257.99 257.30 258.49 260.81 267.09 272.85 278.11 279.14 280.41 284.22 290.51 300.50
    299.01 302.47 311.43 314.20 314.06 313.49
```

R output

Regression models

```
lm(formula = beefconsumption ~ CPI + beefproduction + beefprice +
    poultryprice + inflationbeefprice + inflationpoultryprice)

Residuals:
     Min       1Q    Median      3Q      Max
−0.65710 −0.20653 −0.03942 0.19164 0.72859

Coefficients:
                        Estimate  Std. Error t value Pr(>|t|)
(Intercept)             50.17310  28.68218    1.749 0.103796
CPI                     −0.17944   0.10034   −1.788 0.097044 .
beefproduction           0.04570   0.02543    1.797 0.095514 .
beefprice                1.04853   0.25640    4.089 0.001278 **
poultryprice            −0.19514   0.31671   −0.616 0.548438
inflationbeefprice    −315.74628  70.17710   −4.499 0.000598 ***
inflationpoultryprice   88.71998  85.40920    1.039 0.317850
−−−
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3962 on 13 degrees of freedom
Multiple R-squared: 0.9529,     Adjusted R-squared: 0.9311
F-statistic:  43.8 on 6 and 13 DF, p-value: 6.98e-08

Call:
lm(formula = beefconsumption ~ CPI + beefproduction + beefprice +
    inflationbeefprice  + inflationpoultryprice)

Residuals:
    Min      1Q  Median      3Q     Max
-0.5912 -0.2153 -0.0268 0.2270 0.7728

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)             60.13318   23.16200   2.596 0.021133 *
CPI                     -0.21587    0.07925  -2.724 0.016465 *
beefproduction           0.04149    0.02394   1.733 0.105041
beefprice                0.97423    0.22120   4.404 0.000600 ***
inflationbeefprice    -295.63265   60.73021  -4.868 0.000249 ***
inflationpoultryprice   37.51632   19.26935   1.947 0.071889 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3873 on 14 degrees of freedom
Multiple R-squared: 0.9515,     Adjusted R-squared: 0.9342
F-statistic: 54.92 on 5 and 14 DF, p-value: 1.055e-08

Call:
lm(formula = beefconsumption ~ CPI + beefprice + inflationbeefprice +
    inflationpoultryprice)

Residuals:
     Min       1Q   Median       3Q      Max
-0.52442 -0.20853 -0.04179 0.13892 0.89544

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)             62.46937   24.61861   2.537 0.022755 *
CPI                     -0.21068    0.08432  -2.499 0.024570 *
beefprice                0.97579    0.23551   4.143 0.000867 ***
inflationbeefprice    -306.34538   64.32320  -4.763 0.000252 ***
inflationpoultryprice   53.61460   17.97487   2.983 0.009293 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4123 on 15 degrees of freedom
Multiple R-squared: 0.9411,     Adjusted R-squared: 0.9254
F-statistic:  59.9 on 4 and 15 DF, p-value: 4.82e-09

Call:
lm(formula = beefconsumption ~ CPI + beefproduction + inflationbeefprice +
    inflationpoultryprice)

Residuals:
    Min      1Q  Median      3Q     Max
-1.2684 -0.3275 0.1646  0.3297  0.9735

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)          -36.33745   11.23550  -3.234 0.005561 **
CPI                    0.12422    0.02659   4.672 0.000301 ***
beefproduction         0.04192    0.03572   1.173 0.258909
inflationbeefprice   -33.31451   17.70341  -1.882 0.079411 .
```

```
inflationpoultryprice    50.97689    28.38875    1.796 0.092715 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5779 on 15 degrees of freedom
Multiple R-squared: 0.8843,     Adjusted R-squared: 0.8534
F-statistic: 28.66 on 4 and 15 DF, p-value: 7.215e-07

Call:
lm(formula = beefconsumption ~ CPI + inflationbeefprice + inflationpoultryprice)

Residuals:
     Min       1Q   Median       3Q      Max
-1.25177 -0.31216 0.06467  0.28040  1.09766

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)            -34.13285   11.20706  -3.046 0.007708 **
CPI                      0.13002    0.02643   4.919 0.000154 ***
inflationbeefprice     -43.71449   15.50477  -2.819 0.012337 *
inflationpoultryprice   67.26329   25.05487   2.685 0.016276 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5847 on 16 degrees of freedom
Multiple R-squared: 0.8737,     Adjusted R-squared: 0.85
F-statistic: 36.88 on 3 and 16 DF, p-value: 2.042e-07

Call:
lm(formula = beefconsumption ~ CPI + beefproduction + beefprice +
    poultryprice)

Residuals:
    Min      1Q  Median      3Q     Max
-1.3635 -0.3231 0.1091  0.3691  1.0538

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)    -29.54224    8.62143  -3.427  0.00375 **
CPI              0.09935    0.01599   6.211 1.67e-05 ***
beefproduction   0.04583    0.03811   1.203  0.24775
beefprice       -0.09627    0.06636  -1.451  0.16744
poultryprice     0.15636    0.11045   1.416  0.17731
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6014 on 15 degrees of freedom
Multiple R-squared: 0.8747,   Adjusted R-squared: 0.8413
F-statistic: 26.17 on 4 and 15 DF, p-value: 1.299e-06

Call:
lm(formula = beefconsumption ~ CPI + beefprice + poultryprice)

Residuals:
    Min      1Q  Median      3Q     Max
-1.3454 -0.3174 0.1083  0.2109  1.1987

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  -25.61689    8.09028  -3.166  0.00599 **
CPI            0.09892    0.01621   6.102 1.53e-05 ***
beefprice     -0.13883    0.05692  -2.439  0.02674 *
poultryprice   0.22627    0.09522   2.376  0.03032 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 0.6097 on 16 degrees of freedom
Multiple R−squared: 0.8626,   Adjusted R−squared: 0.8368
F−statistic: 33.48 on 3 and 16 DF, p−value: 3.975e−07
```

Regression models, outlier removed

```
> poultryprice=poultryprice[−c(6)]
> CPI=CPI[−c(6)]
> beefprice=beefprice[−c(6)]
> inflationbeefprice=inflationbeefprice[−c(6)]
> inflationpoultryprice=inflationpoultryprice[−c(6)]
> beefproduction=beefproduction[−c(6)]

Call:
lm(formula = beefconsumption ~ CPI + beefproduction + beefprice +
    poultryprice + inflationbeefprice + inflationpoultryprice)

Residuals:
      Min        1Q    Median        3Q       Max
−0.41194 −0.25070 −0.06312 0.11936 0.48614

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)               55.43497   24.06947   2.303 0.039971 *
CPI                       −0.19072    0.08401  −2.270 0.042429 *
beefproduction             0.03138    0.02198   1.428 0.178824
beefprice                  0.92700    0.21955   4.222 0.001184 **
poultryprice              −0.05119    0.27068  −0.189 0.853159
inflationbeefprice      −278.17005   60.47423  −4.600 0.000611 ***
inflationpoultryprice     44.59314   73.45154   0.607 0.555092
−−−
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3313 on 12 degrees of freedom
Multiple R−squared: 0.9696,    Adjusted R−squared: 0.9543
F−statistic: 63.69 on 6 and 12 DF, p−value: 2.116e−08

Call:
lm(formula = beefconsumption ~ CPI + beefproduction + beefprice +
    inflationbeefprice + inflationpoultryprice)

Residuals:
      Min        1Q    Median        3Q       Max
−0.39166 −0.25417 −0.04663 0.13013 0.47616

Coefficients:
                          Estimate Std. Error t value Pr(>|t|)
(Intercept)               58.01601   19.07687   3.041 0.009459 **
CPI                       −0.20004    0.06547  −3.055 0.009203 **
beefproduction             0.03011    0.02013   1.496 0.158574
beefprice                  0.90649    0.18368   4.935 0.000272 ***
inflationbeefprice      −272.54682   50.66921  −5.379 0.000126 ***
inflationpoultryprice     31.06387   16.02824   1.938 0.074642 .
−−−
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3187 on 13 degrees of freedom
Multiple R−squared: 0.9695,    Adjusted R−squared: 0.9577
F−statistic: 82.54 on 5 and 13 DF, p−value: 2.207e−09

Call:
lm(formula = beefconsumption ~ CPI + beefprice + inflationbeefprice +
    inflationpoultryprice)
```

```
Residuals:
     Min       1Q   Median       3Q      Max
-0.50856 -0.17154 -0.05439 0.10058 0.55363

Coefficients:
                        Estimate Std. Error t value Pr(>|t|)
(Intercept)              59.4069    19.8785   2.989 0.009772 **
CPI                      -0.1947     0.0682  -2.855 0.012735 *
beefprice                 0.9001     0.1916   4.699 0.000342 ***
inflationbeefprice     -277.4493    52.7505  -5.260 0.000121 ***
inflationpoultryprice    41.5459    15.0389   2.763 0.015264 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.3325 on 14 degrees of freedom
Multiple R-squared: 0.9642,     Adjusted R-squared: 0.954
F-statistic: 94.28 on 4 and 14 DF, p-value: 5.835e-10
```

Price elasticity models

```
lm(formula = (beefconsumption) ~ (beefprice))

Residuals:
     Min       1Q   Median       3Q      Max
-2.15908 -1.14190 -0.08212 0.59404 2.63923

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  17.4609     0.8934   19.54  < 2e-16 ***
beefprice   -10.3831     0.9898  -10.49 4.82e-12 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.357 on 33 degrees of freedom
Multiple R-squared: 0.7693,     Adjusted R-squared: 0.7623
F-statistic:   110 on 1 and 33 DF, p-value: 4.823e-12

Call:
lm(formula = log(beefconsumption) ~ log(beefprice))

Residuals:
     Min       1Q   Median       3Q      Max
-0.31765 -0.11780 0.01575  0.09629  0.27294

Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)     1.85940    0.03234   57.49  < 2e-16 ***
log(beefprice) -1.23392    0.10486  -11.77 2.37e-13 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1595 on 33 degrees of freedom
Multiple R-squared: 0.8075,     Adjusted R-squared: 0.8017
F-statistic: 138.5 on 1 and 33 DF, p-value: 2.37e-13
```

AR(1)-model

```
lm(formula = consumption ~ consumptionlag)

Residuals:
     Min       1Q   Median       3Q      Max
-1.03006 -0.21378 -0.01757 0.18792 1.47751
```

```
Coefficients:
               Estimate Std. Error t value Pr(>|t|)
(Intercept)     0.24898    0.30172   0.825    0.415
consumptionlag  0.99622    0.03466  28.739   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5427 on 32 degrees of freedom
Multiple R-squared: 0.9627,     Adjusted R-squared: 0.9615
F-statistic: 825.9 on 1 and 32 DF,  p-value: < 2.2e-16
```

Error correction model

```
lm(formula = diff.consumption ~ residuals + diff.price, data = data)

Residuals:
     Min       1Q   Median       3Q      Max
-0.97482 -0.23739 -0.04282  0.21965  1.10318

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.21598    0.08492   2.543   0.0162 *
residuals   -0.08353    0.06753  -1.237   0.2254
diff.price  -2.97258    1.61208  -1.844   0.0748 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.4872 on 31 degrees of freedom
Multiple R-squared: 0.1205,     Adjusted R-squared: 0.06371
F-statistic: 2.123 on 2 and 31 DF,  p-value: 0.1368
```

Tests on price elasticity model

```
Empirical Fluctuation Process: OLS-based CUSUM test

Call: efp(formula = priceelasticity, data = data, type = "OLS-CUSUM")

> bound.ocus <- boundary(ocus,alpha=0.05)
>  bound.ocus
Time Series:
Start = c(0, 1)
End = c(1, 1)
Frequency = 35
 [1] 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581
[12] 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581
[23] 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581
[34] 1.3581 1.3581 1.3581

> sctest(ocus)

        OLS-based CUSUM test

data:  ocus
S0 = 1.5166, p-value = 0.0201

> rcus

Empirical Fluctuation Process: Recursive CUSUM test

Call: efp(formula = priceelasticity, data = data, type = "Rec-CUSUM")

> bound.rcus <- boundary(rcus,alpha=0.05)
```

```
> bound.rcus
Time Series:
Start = c(0, 1)
End = c(1, 1)
Frequency = 33
 [1] 0.9478981 1.0053465 1.0627948 1.1202432 1.1776916 1.2351400 1.2925883 1.3500367
 [9] 1.4074851 1.4649334 1.5223818 1.5798302 1.6372785 1.6947269 1.7521753 1.8096236
[17] 1.8670720 1.9245204 1.9819688 2.0394171 2.0968655 2.1543139 2.2117622 2.2692106
[25] 2.3266590 2.3841073 2.4415557 2.4990041 2.5564525 2.6139008 2.6713492 2.7287976
[33] 2.7862459 2.8436943

> sctest(rcus)

        Recursive CUSUM test

data:  rcus
S = 2.4233, p-value = 1.253e-10

> fs

F statistics

Call: Fstats(formula = priceelasticity , data = data)

> bound.fs
Time Series:
Start = c(0, 6)
End = c(0, 31)
Frequency = 35
 [1] 11.64361 11.64361 11.64361 11.64361 11.64361 11.64361 11.64361 11.64361 11.64361
[10] 11.64361 11.64361 11.64361 11.64361 11.64361 11.64361 11.64361 11.64361 11.64361
[19] 11.64361 11.64361 11.64361 11.64361 11.64361 11.64361 11.64361 11.64361

> sctest(fs,type="expF")

        expF test

data:  fs
exp.F = 19.0956, p-value = 1.075e-05

> sctest(fs,type="supF")

        supF test

data:  fs
sup.F = 42.2122, p-value = 2.715e-08

> sctest(fs,type="aveF")

        aveF test

data:  fs
ave.F = 20.1625, p-value = 5.406e-05
```

Tests on AR(1)-model

```
> ocus <- efp(ARmodel,type="OLS-CUSUM",data=data)
> ocus

Empirical Fluctuation Process: OLS-based CUSUM test

Call: efp(formula = ARmodel, data = data, type = "OLS-CUSUM")

> bound.ocus <- boundary(ocus,alpha=0.05)
> bound.ocus
```

```
Time Series:
Start = 1
End = 35
Frequency = 1
 [1]  1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581
[12]  1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581
[23]  1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581
[34]  1.3581 1.3581

> sctest(ocus)

        OLS-based CUSUM test

data:  ocus
S0 = 0.6598, p-value = 0.7767

> rcus <- efp(ARmodel,type="Rec-CUSUM",data=data)
> rcus

Empirical Fluctuation Process: Recursive CUSUM test

Call: efp(formula = ARmodel, data = data, type = "Rec-CUSUM")

> bound.rcus <- boundary(rcus,alpha=0.05)
>  bound.rcus
Time Series:
Start = 3
End = 35
Frequency = 1
 [1]  0.9478981 1.0071417 1.0663854 1.1256290 1.1848726 1.2441163 1.3033599 1.3626035
 [9]  1.4218472 1.4810908 1.5403344 1.5995780 1.6588217 1.7180653 1.7773089 1.8365526
[17]  1.8957962 1.9550398 2.0142835 2.0735271 2.1327707 2.1920144 2.2512580 2.3105016
[25]  2.3697453 2.4289889 2.4882325 2.5474761 2.6067198 2.6659634 2.7252070 2.7844507
[33]  2.8436943

> sctest(rcus)

        Recursive CUSUM test

data:  rcus
S = 0.7356, p-value = 0.2039

> fs

F statistics

Call: Fstats(formula = ARmodel, data = data)

>  bound.fs
Time Series:
Start = 6
End = 30
Frequency = 1
 [1]  11.59453 11.59453 11.59453 11.59453 11.59453 11.59453 11.59453 11.59453 11.59453
[10]  11.59453 11.59453 11.59453 11.59453 11.59453 11.59453 11.59453 11.59453 11.59453
[19]  11.59453 11.59453 11.59453 11.59453 11.59453 11.59453 11.59453

>  sctest(fs,type="expF")

        expF test

data:  fs
exp.F = 3.3563, p-value = 0.04261

> sctest(fs,type="supF")
```

```
        supF test

data:  fs
sup.F = 11.6532, p-value = 0.04879

> sctest(fs,type="aveF")

        aveF test

data:  fs
ave.F = 2.6206, p-value = 0.2382
```

Tests on error correction model

```
> ocus

Empirical Fluctuation Process: OLS-based CUSUM test

Call: efp(formula = ecm, data = data, type = "OLS-CUSUM")

>  bound.ocus <- boundary(ocus,alpha=0.05)
>  bound.ocus
Time Series:
Start = 1
End = 35
Frequency = 1
 [1]  1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581
[12]  1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581
[23]  1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581 1.3581
[34]  1.3581 1.3581

>  sctest(ocus)

        OLS-based CUSUM test

data:  ocus
S0 = 0.7099, p-value = 0.6947

> rcus

Empirical Fluctuation Process: Recursive CUSUM test

Call: efp(formula = ecm, data = data, type = "Rec-CUSUM")

> bound.rcus <- boundary(rcus,alpha=0.05)
>  bound.rcus
Time Series:
Start = 4
End = 35
Frequency = 1
 [1]  0.9478981 1.0090528 1.0702075 1.1313623 1.1925170 1.2536717 1.3148264 1.3759811
 [9]  1.4371358 1.4982905 1.5594453 1.6206000 1.6817547 1.7429094 1.8040641 1.8652188
[17]  1.9263736 1.9875283 2.0486830 2.1098377 2.1709924 2.2321471 2.2933019 2.3544566
[25]  2.4156113 2.4767660 2.5379207 2.5990754 2.6602302 2.7213849 2.7825396 2.8436943

> sctest(rcus)

        Recursive CUSUM test

data:  rcus
S = 0.4827, p-value = 0.6661

> fs
```

```
F statistics

Call: Fstats(formula = ecm, data = data)

> bound.fs
Time Series:
Start = 6
End = 30
Frequency = 1
 [1] 13.91463 13.91463 13.91463 13.91463 13.91463 13.91463 13.91463 13.91463 13.91463
[10] 13.91463 13.91463 13.91463 13.91463 13.91463 13.91463 13.91463 13.91463 13.91463
[19] 13.91463 13.91463 13.91463 13.91463 13.91463 13.91463 13.91463

> sctest(fs,type="expF")

        expF test

data:  fs
exp.F = 1.3429, p-value = 0.6538

> sctest(fs,type="supF")

        supF test

data:  fs
sup.F = 5.2935, p-value = 0.7656

> sctest(fs,type="aveF")

        aveF test

data:  fs
ave.F = 2.0732, p-value = 0.6702
```

R plots

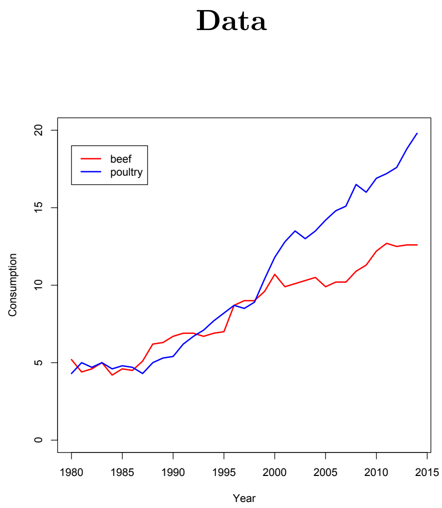

Figure 1: Direct consumption in kg per person and year (2014 is preliminary)

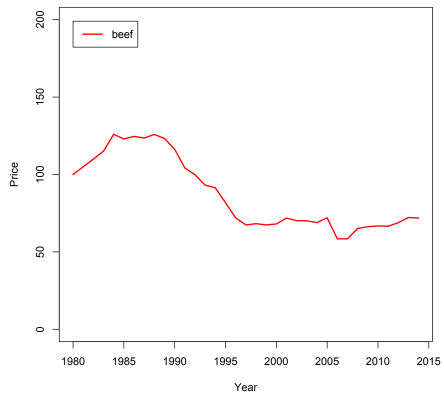

Figure 2: Price index with base year 1980 (adjusted for inflation)

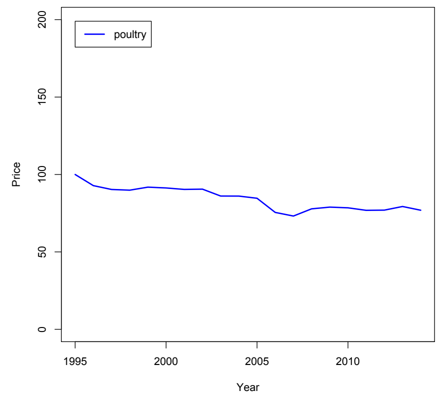

Figure 3: Price index with base year 1995 (adjusted for inflation)

Regression model

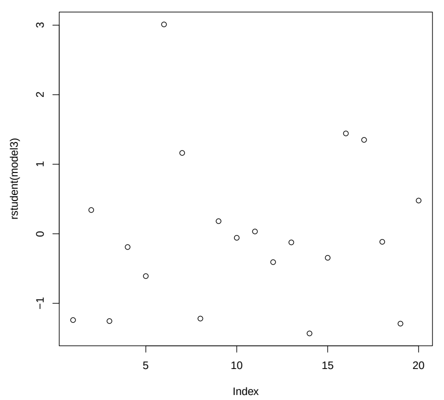

Figure 4: Regression model: Rstudent of final model

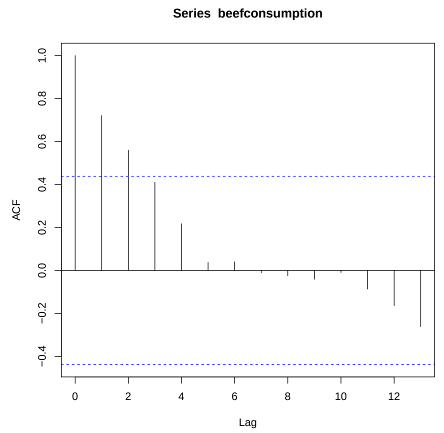

Figure 5: Regression model: ACF

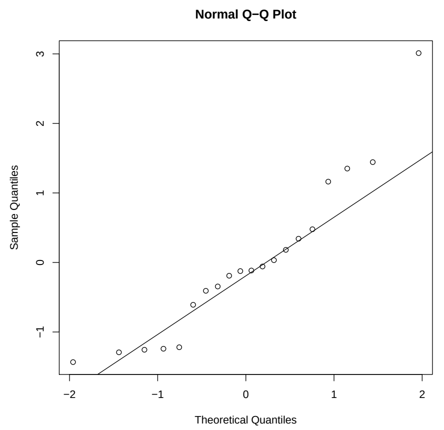

Figure 6: Regression model: Normal-QQ plot of final model

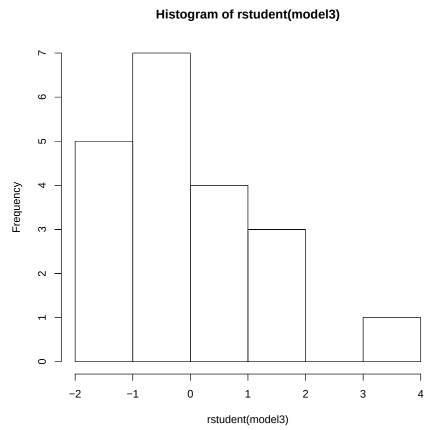

Figure 7: Regression model: Histogram of rstudent of final model

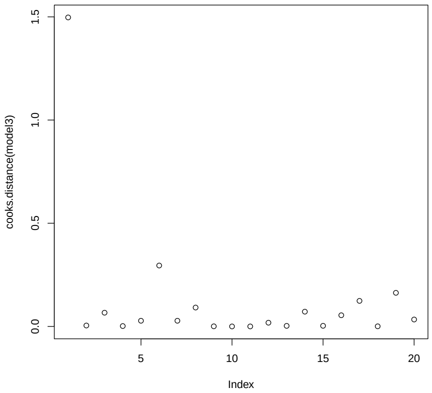

Figure 8: Regression model: Cooks distance of final model

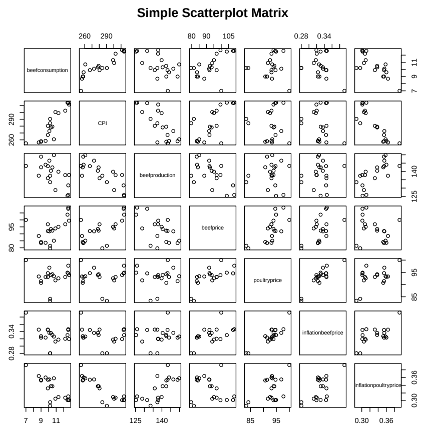

Figure 9: Regression model: Scatterplot matrix

Price elasticity model

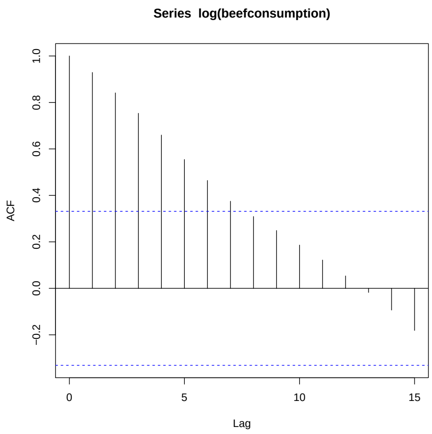

Figure 10: Price elasticity model (log transformed): ACF

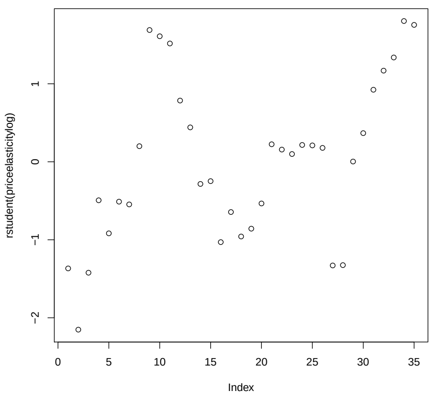

Figure 11: Price elasticity model (log transformed): Rstudent of price elasticity model

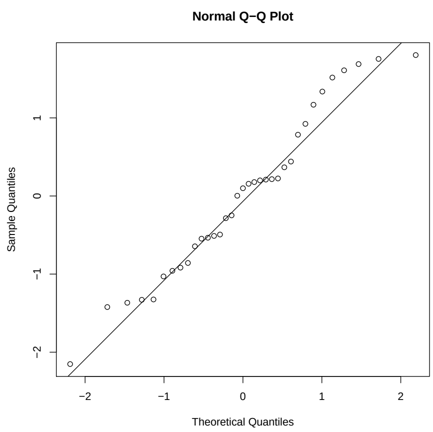

Figure 12: Price elasticity model (log transformed): Normal QQ-plot of price elasticity model

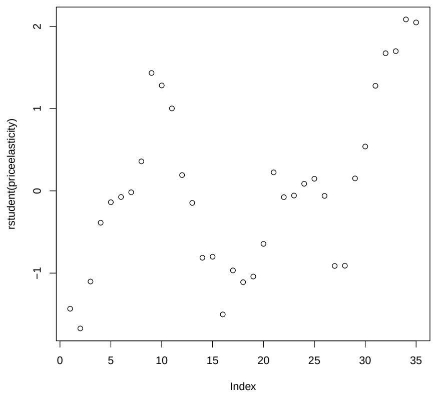

Figure 13: Price elasticity model: Rstudent of price elasticity model

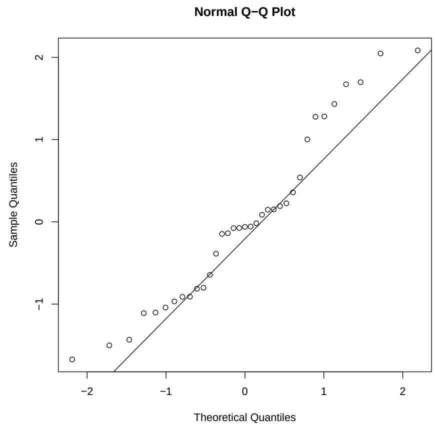

Figure 14: Price elasticity model: Normal QQ-plot of price elasticity model

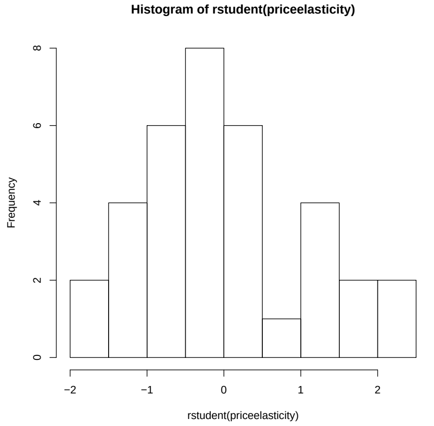

Figure 15: Price elasticity model: Histogram of rstudent

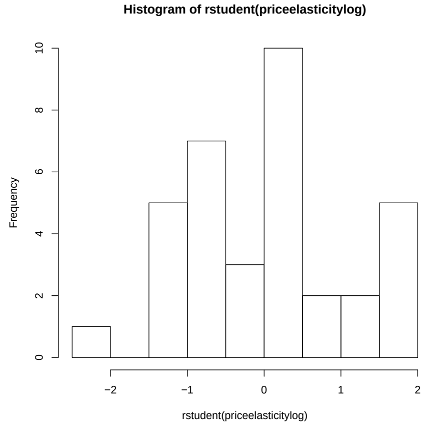

Figure 16: Price elasticity model (log transformed): Histogram of rstudent

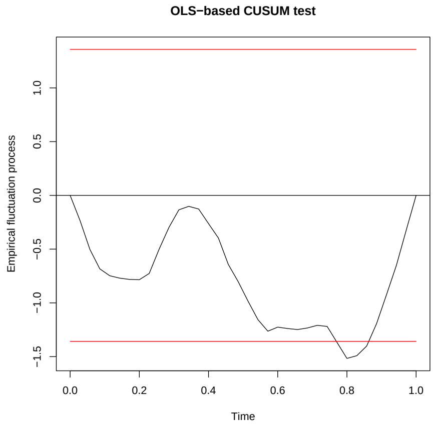

Figure 17: Price elasticity model: OLS-CUSUM

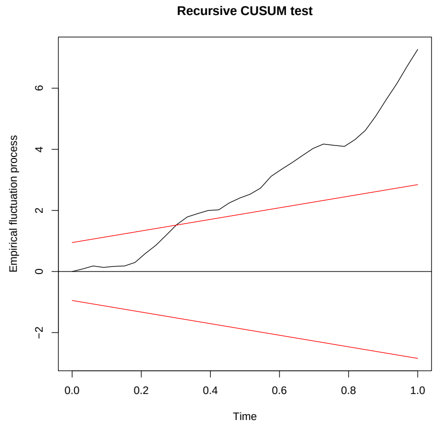

Figure 18: Price elasticity model: Rec-CUSUM

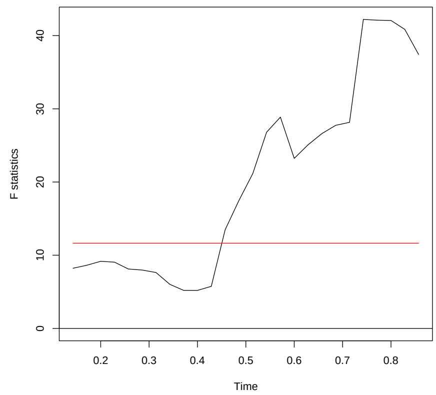

Figure 19: Price elasticity model: supF

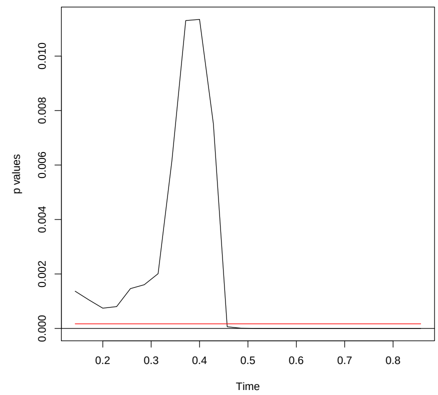

Figure 20: Price elasticity model: F-test (p-value)

AR(1)-model

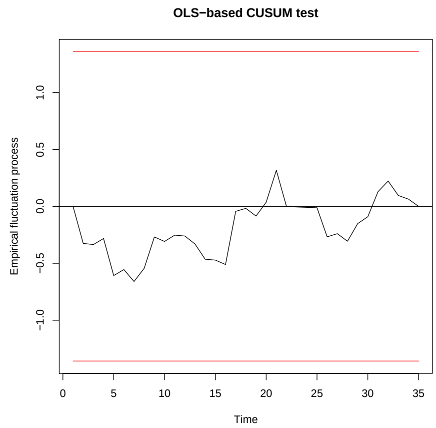

Figure 21: AR(1)-model: OLS-CUSUM

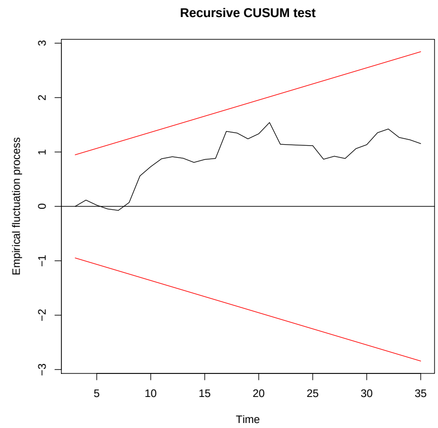

Figure 22: AR(1)-model: Rec-CUSUM

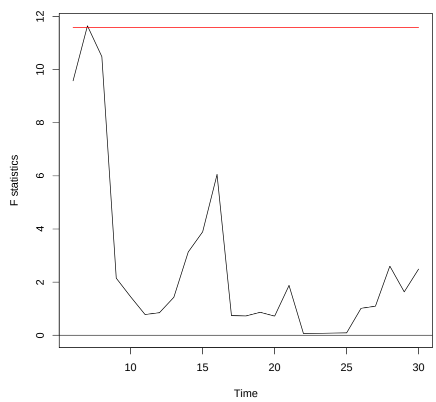

Figure 23: AR(1)-model: supF

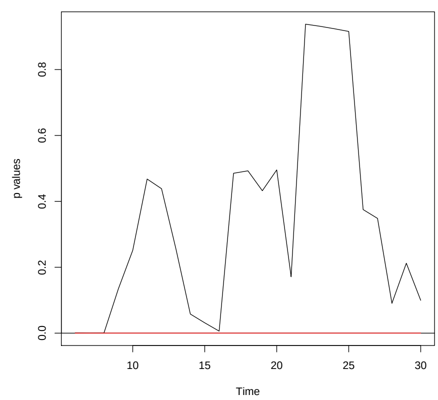

Figure 24: AR(1)-model: F-test (p-value)

Error correction model

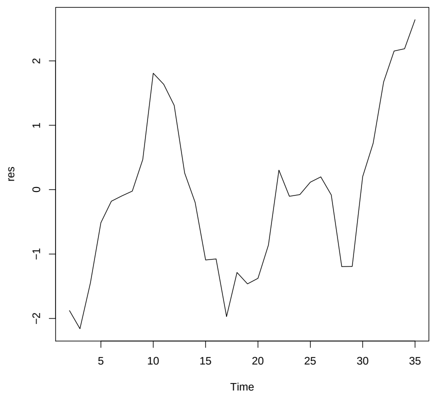

Figure 25: Error correction model: cointegrated residuals

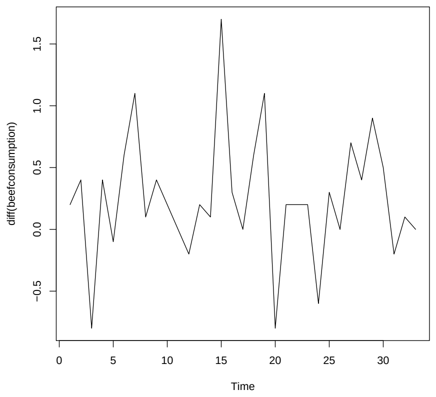

Figure 26: Error correction model: diffconsumption

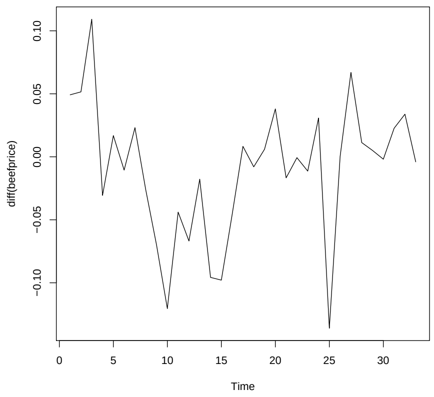

Figure 27: Error correction model: diffprice

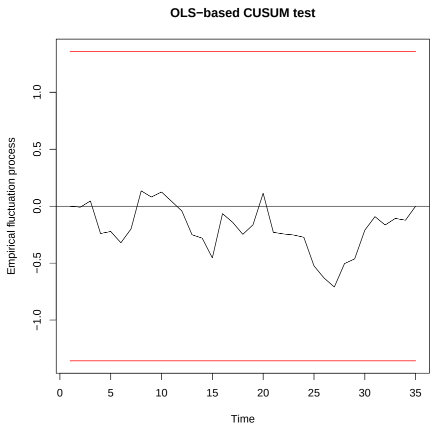

Figure 28: Error correction model: OLS-CUSUM

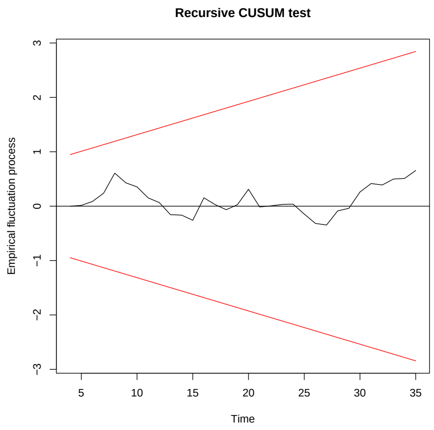

Figure 29: Error correction model: Rec-CUSUM

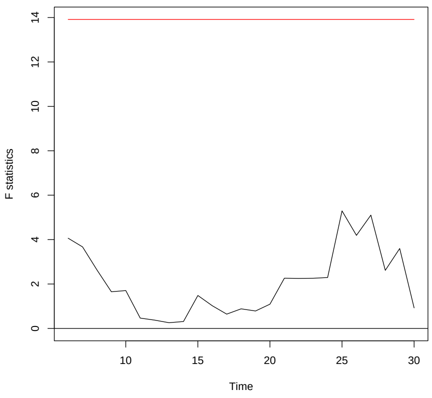

Figure 30: Error correction model: supF

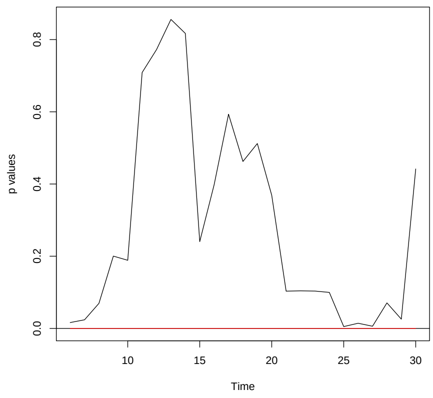

Figure 31: Error correction model: F-test (p-value)