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Price transmission

Price transmission from Norwegian export to German and Spanish market for salmon products

Syed Mohsin Raza

Supervisor: Frank Asche

Master thesis, Industrial Economics

University of Stavanger

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Syed Mohsin Raza

Abstract

This thesis analyzes the price transmission from Norwegian export of salmon to retail products in Germany and Spain. The thesis shows the relationship between the export prices and the retail prices as well as the degree of the relationship. With export of salmon and the sale at retail level we are looking at the beginning and the end of the supply chain. In between these supply chain levels the price is transmitted and at some levels the transmission decreases. This means that for several reasons the price transmission not always is complete from export to retail. This thesis focuses on the relationship between the export and retail as well as testing for other factors that can help us understand the potential patterns and differences in different product categories. It is also studied for potential patterns and differences in prepacked and non-prepacked salmon products. The assumptions made before the analyses was that the price transmission would decrease as the processing increased.

The results from the analyses show that there is a relationship between the export and retail price for some of the product categories. While some had no relationship. This shows that the salmon markets in Germany and Spain are different for the product categories. The markets change over time and these results may be very different in a few years. However, for the time being there were not enough relationships for us to be able to uncover the potential patterns mentioned.

For the prepacked and non-prepacked salmon the results show that the price transmission is higher for the non-prepacked salmon compared to the prepacked salmon. This can be explained by the fact that the non-prepacked salmon product that is bought are packed at the retail level removing the packing step from the supply chain.

Keywords – Price transmission, Markets, Time series econometrics, cointegration analysis

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1 Introduction

The seafood export has seen an increase in the last 30-40 years. Decreasing costs on transportation and effectiveness in logistics have given the seafood industry more possibilities than before. With effective transportation, producers have the option to sell fresh seafood across the globe. All levels in the supply chain have seen this increase in effectiveness. Simultaneously supermarkets have replaced fish markets and fishmongers. The supply of seafood increased from 71.7 million metric tons in 1976 to 159.9 million metric tons in 2006, doubling the seafood supply. At the same time the share of aquaculture increased where wild fish was the main source of supply.(Anderson et al., 2010)

While efficiency in production has increased for many years it has stagnated, and the growth in demand has been just as important factor to the increase in export of salmon as the production efficiency. Growth in export and demand has lead to increase in prices as well. The increase in export prices leads to a question of price transmission. There has been conducted several studies such as (Asche et al. 2011, Asche et al. 1999, Asche et al. 2007, Thong et al. 2019, Tveterås & Asche 2008, and Tveterås et al. 2017) about price transmission for seafood. There is, however, still several aspects of price transmission and several other markets to analyze. These studies have been used as inspiration for writing the thesis and the methodology.

For our analysis we are looking at the prices in Germany and Spain. Two countries with different cuisines. Both countries being among the top 20 seafood consuming countries in the world. With Spain being the 5th highest and Germany the 19th (Norwegian seafood council, 2020). Naturally when speaking of Norwegian export of seafood, salmon stands out as a popular food. As these countries have different cuisines the retail products containing salmon will also be very different. Because of the variety the price transmission will also vary between the countries and each product category.

Going forward with the assumption of there being price transmission between the export price and the retail prices is natural as the salmon exported is in most cases the main or the most important ingredient in the products. For raw salmon sold in the countries we expect high degree of price transmission. While we expect less for products with more steps before the final products. We can rate the expectancy from natural salmon having the highest, then smoked salmon, and finally having the lowest expected price transmission, prepared salmon. We expect less price transmission from export to products with more steps involved as all the steps between the final consumer and the producer has a cost that affects the final price on the retail product. The steps mentioned can be preparation of product, storage, packaging, market position, etc.

1.1 Problem definition

Using data for export prices and retail prices for products in Germany and Spain i will study the price transmission between these levels in the supply chain. In this study i will use the framework that has been set by earlier mentioned studies dedicated to price transmission analysis. The study will be done using econometric analysis tools set for time series data. The main focus will be on the cointegration between the export and retail prices. Because of non-stationarity issues we cannot rely on OLS regression alone and will have to use cointegration analysis to be able to come to an appropriate conclusion. We will in addition to a cointegration analysis do several other analyses that can strengthen our conclusion in some cases.

For the cointegration we will take use of the Johansen cointegration test. further we will test for the law of one price using the Johansen framework. Further tests will include a test for exogeneity and an ols regression to determine the price tranmission elasticity, or in other words how much the price change in export changes the price for retail products. The models will be estimated once more using a vector error correction model and compared with previous model.

The problem definition is: **Conducting a price transmission analysis for Norwegian export prices to retail prices in Germany and Spain using econometric analyses**.

In the next section i will go through some relevant price theory that sets up for our price transmission analysis of export to retail prices in Germany and Spain.

2 Theory

For this thesis the focus is price transmission. Price transmission is how a change in price in one part of the supply chain is transferred to another part of the supply chain. E.g. How an increase in export price impacts the price of a product bound to the exported commodity. In our case the commodity is whole fresh salmon and at the retail level it is several different salmon product categories.

To understand how there might be price transmission from whole fresh salmon to other parts of the supply chain we need to have a look at price theory. It is safe to assume that there is some degree of price transmission from salmon export prices and prices for salmon products, but this is not always the case as there may not be complete price transmission because of changes or inputs in to the products.

A large part of the price for a product at retail level depends on value added to the product. In our case this can range from just packing and shipping to fully developed meals containing salmon. We assume that the products sold with little to no value added will have a higher degree of price transmission from the export price to retail price than the products that have been heavily altered or prepared.

A starting point for this subject is demand and supply. Price transmission can be explained by looking at derived demand (Tomek & Kaiser, 2014). Derived demand is similarly to consumer demand a downward sloping curve which instead of describing demand for a product. It tells us the demand for a product that another product depends on. An example of this is can be demand of salmon increasing because demand of salmon fillets increasing. The change can be illustrated with a simple demand graph with the demand for a farm level product, e.g. fresh whole Norwegian salmon, and the demand for retail level product, e.g. smoked salmon. When the demand for smoked salmon increases the demand curve will shift to the right increasing the price of the smoked salmon, and since you cannot make smoked salmon without fresh whole salmon the demand for fresh whole salmon also shift to the right.

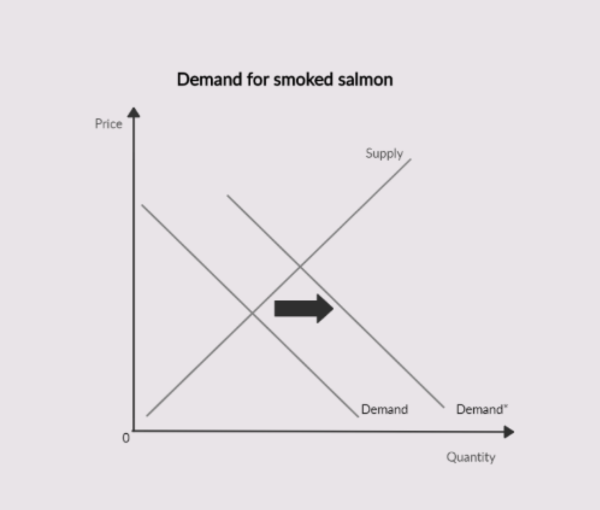


Figure 2.1: Demand for smoked salmon

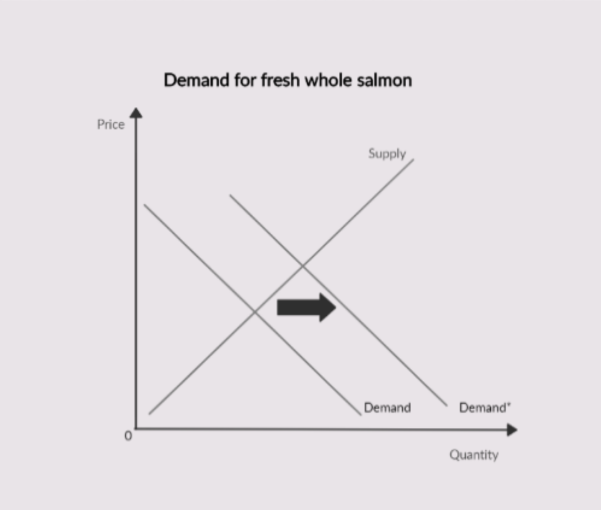


Figure 2.2: Demand for fresh whole salmon

Similarly to changes in demand, changes in supply can also affect the price. In the case of supply the changes there are several reasons as to why the supply would change. In our instance the most relevant would be because of increased costs at the production level. Increased costs at farm level would make the producers less eager to sell at the current price level shifting the supply curve to the left. Which gives us a higher price and a lower supply. And subsequently the prices at retail level would react accordingly and also shift to the left.

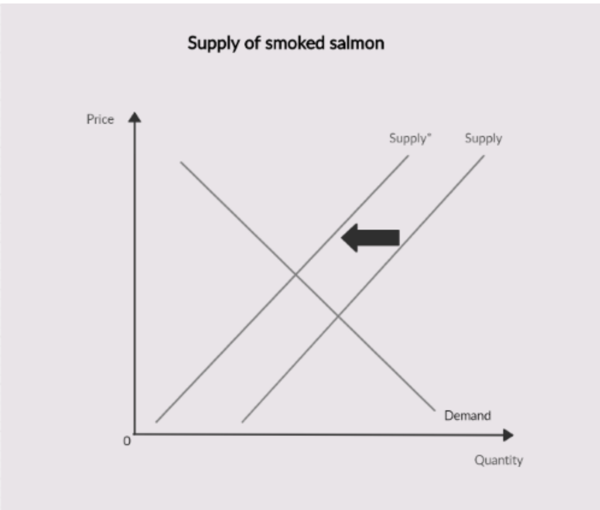


Figure 2.3: Supply of smoked salmon

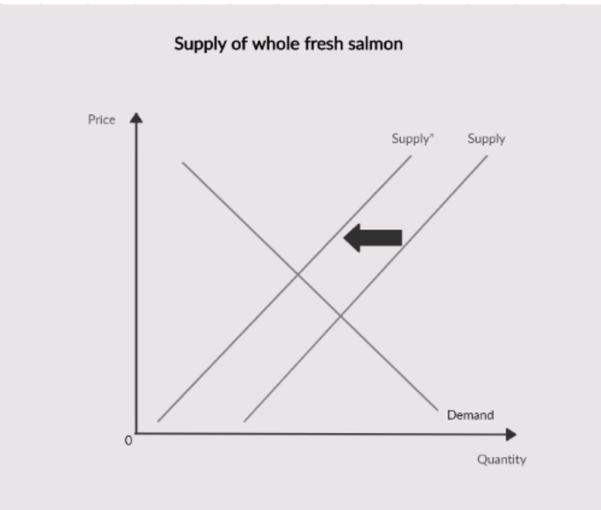


Figure 2.4: Supply of fresh whole salmon

We assume that a firm would aim to maximize their profits. By using the profit maximization we can find the demand and derived demand quantities. This gives the producer a base for the quantity they should produce at retail level and the amount of the commodity they need to buy. The equation can be given as per Tomek Kaiser. (2014):

$$\pi = P_r q_r - P_f q_f - P_m q_m \tag{2.1}$$

P_r is the price for the retail product P_f is the price for the commodity and P_m is the price for other inputs to the product. The q's are the respective quantities. q_r can be given as a function of q_f and q_m. Giving us an updated equation 2.2. By partially derivating the equation for the the firm can find the optimal quantities.

$$\pi = P_r f(q_f, q_m) - P_f q_f - P_m q_m \tag{2.2}$$

The quantity for the other variables q_m is called the marketing margin. Marketing margin is the cost of turning a commodity to a retail product is the range between the commodity price and the retail product price. This is shown visually in figure 2.3. The demand is more volatile for commodities than for retail products. This is shown in equation 2.3.

Figure 2.5: Graph of marketing margin

The elasticity at retail level, given that the marketing margin M is constant, can be given as:

$$E_r = E_f \frac{P_f}{P_r} \tag{2.3}$$

Here E_r is the elasticity at retail level. E_f is the elasticity at farm level, while P_f and P_r are prices at farm and retail level. Since the price at farm level is lower than the price at retail level the ratio of prices will be lower than one giving us a higher elasticity at farm level than retail level.

This is a simplified way of seeing the price transmission. We also have to consider reasons such as labour costs and production costs. For our analysis it is natural to focus on the value added to the product. We are looking to see if there is price transmission from export to retail and therefore the value added is more relevant than other reasons for demand change.

To find how the prices react to changes relative to one another we will use price transmission analysis tools. We will go through all the analyses that are required to get a better understanding of price transmission occurrence. OLS regression, and cointegration tests along with earlier mentioned tests will be used to determine price transmission from commodity to retail product.

3 Data

In this chapter i will review the data set i will use to do the analysis.

To be able to analyze the price transmission from the different stages of the supply chain it is important to have sufficient data. In this thesis i will use both volume and price to get an understanding and overview of the market, and use price per kilo to do the analysis. The data is provided by the Norwegian Seafood Council.

The data set contains export of salmon from Norway to Spain and Germany. Price and volume exported was divided in to months from year 2000 to year 2019. Another set of data contained natural, smoked and prepared salmon. The data also specifies if the product is frozen or fresh. This has data from 2005 to 2019. The price per kilo for the salmon was calculated by dividing the value of the export by the amount exported. The export price is converted from NOK to EUR for the sake of the analysis. The exchange rate used to convert NOK to EUR was 1 NOK = 0.087 EUR per 15. April. 2020.

3.1 German Data

3.1.1 Export to German Market

The Norwegian export to Germany has shown a gradual growth going from 18.9 thousand tons in year 2000 to 37.7 thousand tons in year 2019. The value of the export went from 631 million NOK to 2.3 billion NOK from year 2000 to year 2019. Whole salmon is exported from Norway and the processing takes place in the recipients country, in this case, Germany. This is more profitable for Norwegian export as well as German retail market, because of high costs related to preparing salmon in Norway.

3.1.2 German Salmon Market

Total sales of salmon products in the German market in year 2019 was approximately 58.85 thousand tons in terms of volume with a value of 1.11 billion euros. The German retail salmon market data we have a variety of products which we can divide them in to three main parts: Natural, prepared and smoked salmon. Out of the options prepared salmon is the least favorite option, where smoked salmon and natural salmon dominates with 93% of the volume and 94% of the value. The prepared salmon contains all salmon products that are not smoked or natural. This involves ready-made meals.

The data ranges like the export price data, from 2009 to 2019 with a monthly increment. In a comparison between the volume exported and value exported we can see how value is added to the salmon when it is smoked. Even though smoked salmon is 44% of the total volume of salmon products, the value of smoked salmon is 51% of the total value. For natural salmon the volume and value behaves in the opposite manner, while prepared is very similar in volume and value.

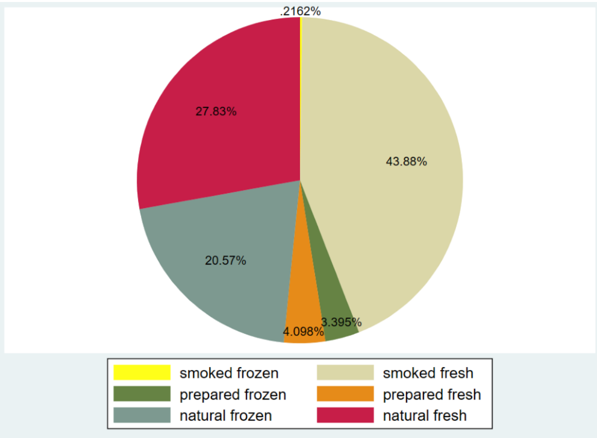


Figure 3.1: Volume pie chart Germany

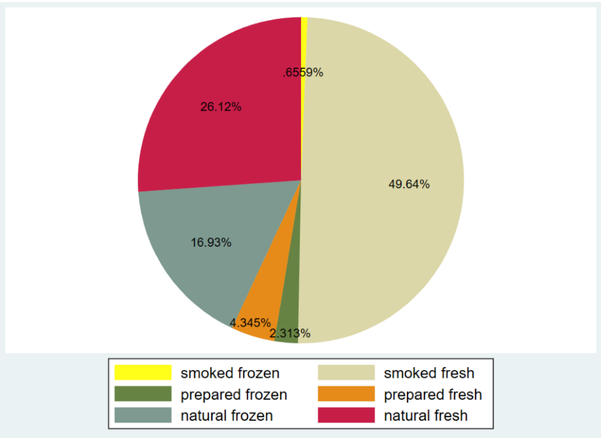


Figure 3.2: Value pie chart Germany

The three main options: Smoked, natural, and prepared are divided into additional two options, this is prepacked(PP) and not prepacked(NPP). The prepacked options are products that are prepacked by suppliers who supply these products to for example grocery stores and supermarkets. Not prepacked products refers to products that are not prepacked, but packed by the grocery store or supermarket them self. A large part of natural salmon sales comes from not prepacked salmon.

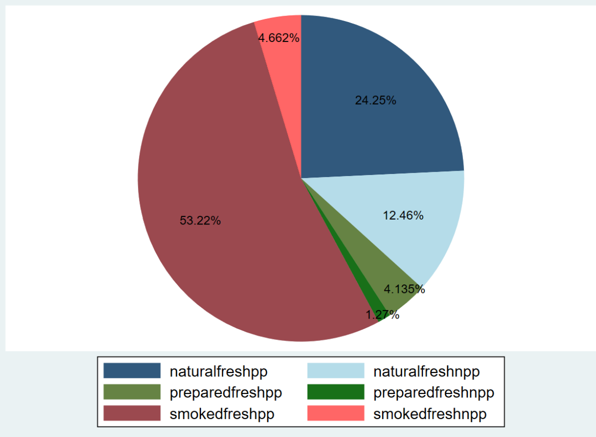


Figure 3.3: Volume pie chart PP vs. NPP Germany

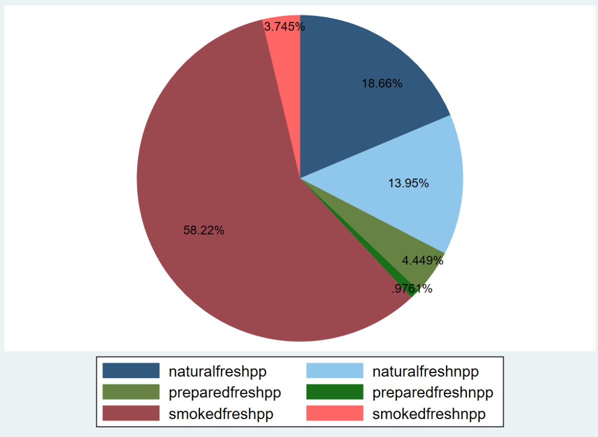


Figure 3.4: Value pie chart PP vs. NPP Germany

3.2 Spanish Data

3.2.1 Export to Spanish Market

Unlike Germany the growth of Norwegian export of salmon to Spain has grown rapidly the last 19 years going from an export of 15.7 thousand tons to 67.2 thousand tons in 2019. The value went from 491 million NOK to 4 billion NOK. While the volume increased 4 times the volume from 2000, the value increased nearly 10 times. This gives us an implication of how the demand for salmon in Spain has increased over the last years. The salmon is exported whole from Norway and the processing is done in Spain.

3.2.2 Spanish Salmon Market

For Spain the total sales in 2019 were approximately 62.4 thousand tons with a value of 830 million euros. The products in the Spanish markets are divided similarly to the German market into three main options. The options are, natural, prepared and smoked. Most of the sales are of these options, either fresh or frozen. The prepared has an additional option of canned salmon. There is also salted and/or dried salmon in the Spanish market, but this is a small volume out of the total salmon sale. The most popular option is natural salmon with approximately 89% of the sales in volume in 2019. Smoked salmon is the second most popular with approximately 10% sales in volume. Prepared salmon has closer to 1% sales in volume, while salted and/or dried is the least favorite with 0.25%

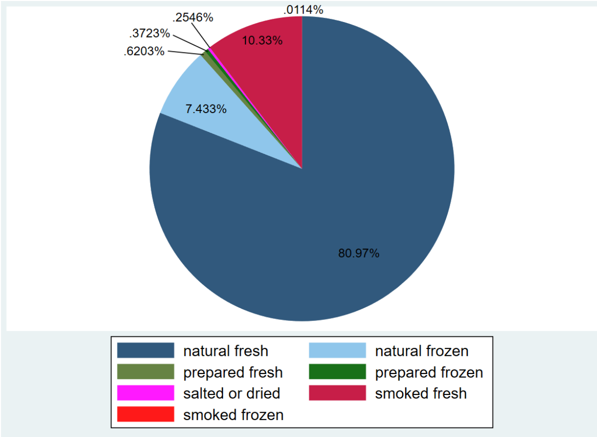


Figure 3.5: Volume pie chart Spain

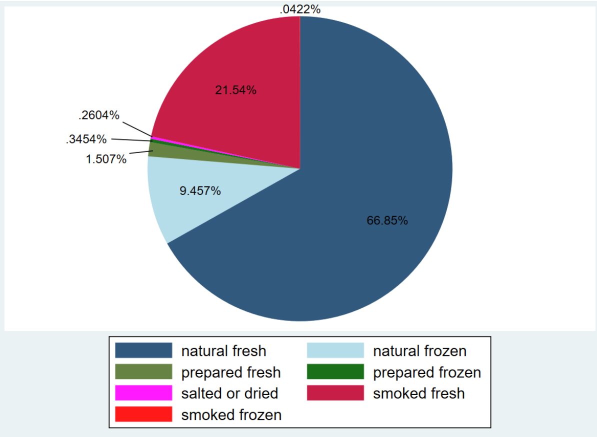


Figure 3.6: Value pie chart Spain

The data ranges from 2009 to 2019 with a monthly increment, similarly to the German data. However, because of missing data and gaps i have chosen to only use the last 5 years of data. So the data in the analysis ranges from 2014-2019. The comparison between volume and value for each option show the earlier mentioned value added in smoked salmon more dramatically in the Spanish market. The volume for smoked salmon was approximately 10% in 2019, but the value of was 22% of the total value of the sales in 2019. This confirms the idea that by adding further steps or further process the salmon the price will increase accordingly.

The salmon is also divided into prepacked and not prepacked, like in the data for Germany. This does not apply to the salted and/or dried salmon, and prepared salmon.

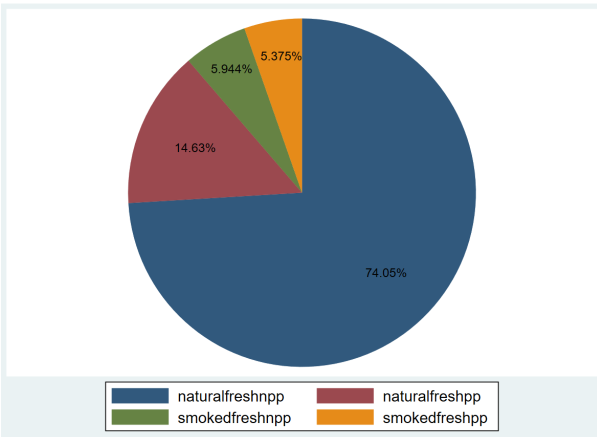


Figure 3.7: Volume pie chart PP vs. NPP Spain

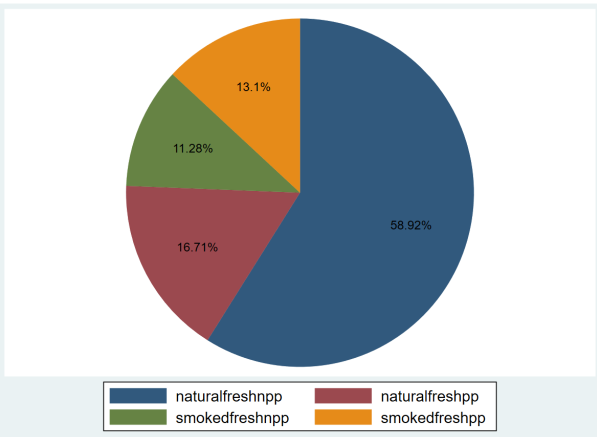


Figure 3.8: Value pie chart PP vs. NPP Spain

3.3 Comparison of German and Spanish market

Germany and Spain have had different rates of growth as mentioned previously in the earlier paragraphs. The data used to compare the export to the countries and the two market spans from 2000 to 2019. In 2000 the export to Germany was higher than in Spain, with 18.9 thousand tons vs 15.6 thousand tons. While in 2019 these numbers have grown for export to both countries, the export to Spain has grown the most. The export volume to Germany in 2019 was 37.7 thousand tons and 67.2 thousand tons in Spain. This is almost double from year 2000 for Germany and more than 4 times as high as year 2000 for Spain. Export to Germany was level from year 2000 until around year 2013 when it started to increase. We can also see some signs of seasonality. In Germany it is very clear with export volume increasing closer to the end of the year, while in Spain it is not necessarily the same. The volume increases during the year, but in many years decreases before the end of the year after hitting max volume somewhere between September and November.

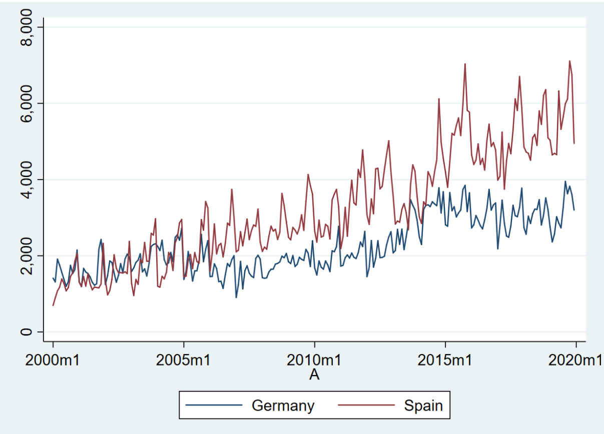


Figure 3.9: Volume exported to Germany and Spain

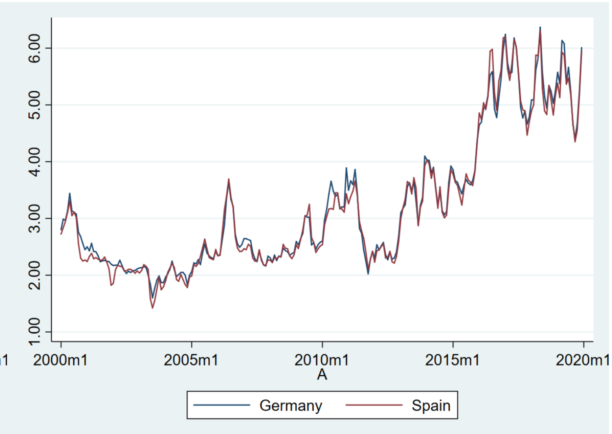
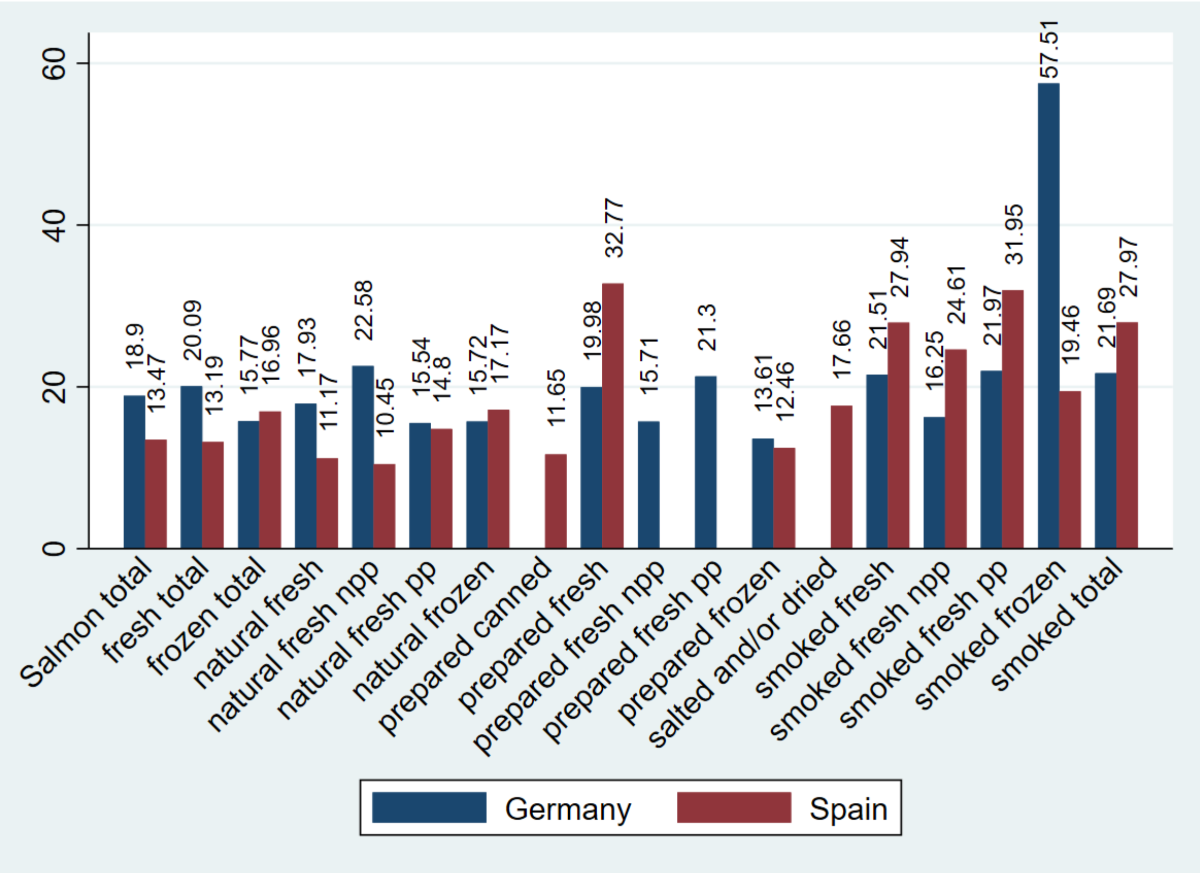


Figure 3.10: Export price in euro to Germany and Spain

The export price per kilo had a similar trend to the volume increase. The price had a level trend until 2013. After 2013 the export price increased a fair amount. When comparing the prices we can see that the export prices are very similar throughout. This is expected, as there should not be any difference in the price for the two countries. The price for the different products in the two countries however, are not that similar. This can be because of different policies, different levels of value added to the products, and/or general differences in price levels in the countries. In addition to this material costs, marketing costs and more.

Figure 3.11: Comparison of Germany and Spain



As seen on figure 3.1 we can see that both countries have very similar data on salmon products. This figure 3.1 compares prices for the products in the two countries. Natural and smoked salmon are naturally very similar. Both have prepared salmon products as well, but here it is difficult for us to decipher if the products in this category are similar or not. This does not make a difference in the analyses. We can start by looking at the figure 3.11 that there is a trend that natural salmon is more expensive in Germany and smoked Salmon is more expensive in Spain. Total salmon sales are more expensive in Germany than Spain, with 18.9 euro per kilo and 13.47 euro per kilo, respectively. Natural frozen salmon which can be seen as the product that is the least processed product are close in price with 15.72 euro per kilo in Germany and 17.17 euro per kilo in Spain. While natural fresh has a larger difference between the prices. The prices are 17.93 in Germany and 11.16 euro. Prepared frozen salmon prices are 13.61 euro in Germany and 12.45 euro in Spain. For prepared fresh salmon the prices are 19.98 and 32.77 for Germany and Spain respectively. When it came to smoked salmon there was a large difference. The price for smoked frozen salmon for Germany was 57.5 euro and 19.46 euro in Spain. The difference in prices in this case are greater than any other product in the data set. For smoked fresh salmon the prices are 21.5 euro in Germany and 27.9 euro in Spain.

4 Methodology

In this chapter i will go through the main concept that are linked to time series econometrics and cointegration analysis. These approaches will be used to do an empirical analysis of the price transmission from export price to retail market price.

4.1 Time series econometrics

4.1.1 Regression

The price transmission analysis is based on time series regression. The standard procedure is used with the following equation (Asche et al. 2014).

$$ln\, p_t^{Retail} = \alpha + \beta\, ln\, p_t^{Export} + e_t \tag{4.1}$$

Here p_t^i is the price in i- market and at time t. The α is the intercept and e_t is the error term, which in our case does not have a significance. The β is what tells us if there is price transmission and the degree of it. If $\beta = 0$ then there is no price transmission between the prices, if $\beta = 1$ then there is complete price transmission. If $\beta \neq 0$ and $\beta \neq 1$, then there is a relationship between the variables to a degree that varies.

Time series data, unlike, cross-sectional data which is gathered at one time, is gathered over different points in time. There is often a time trend on time series data, but can also be mean-reverting. This means that data gathers around a mean, and even with fluctuations go back to the mean. In our case there is a clear time trend on the data. With cross-sectional data there is an assumption that the data is independent of each other. This is not possible with time series. With time series data all the data is dependent of one another. We can see this as the price for one month often is based on the price for the earlier month and the price during the period in which the price is set.

4.1.2 Stationarity

With time series analysis we have to analyze if the data is stationary or non-stationary. A stationary time series will in simple terms not be affected by previous data. In other words the future will be similar to the past and the mean, variance and covariance will stay the same over time. In the context of price there can be stationarity, in some cases, if the price is stable over time and only suffers from short spikes in the price. We can look at stationary process as a first order autoregressive model. An autoregressive model is a time series that is regressed on previous values in the same time series.

$$Y_t = \alpha + \beta_1 Y_{t-1} + \varepsilon_t \tag{4.2}$$

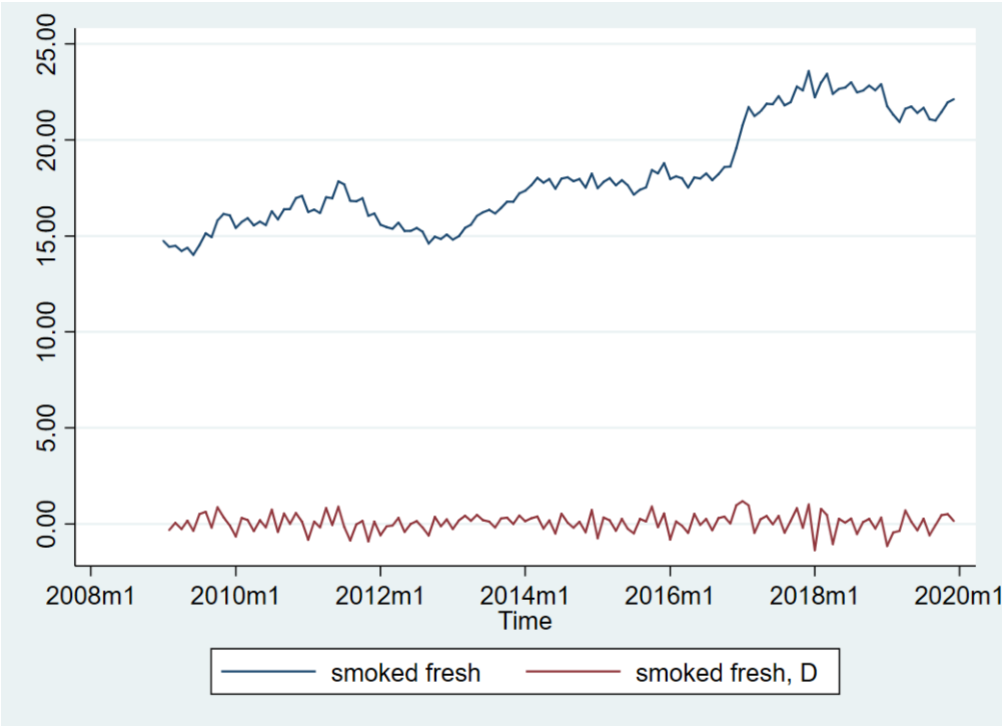
Here we see a standard regression where Y_t is regressed by Y_{t-1}. The error term ε_t is seen as white noise term that is iid, meaning that it is independent and identically distributed. The model is stationary when $\alpha = 0$ and $\beta_1 < 1$.

In most cases, however, price is not a stationary process. A non-stationary process can be explained as a pure random walk:

$$Y_t = Y_{t-1} + \varepsilon_t \tag{4.3}$$

This equation tells us that the value at time t will be equal to the previous period plus a stochastic white noise term that is iid, meaning that it is independent and identically distributed. This equation is the autoregressive equation in first order with a $\alpha= 0$ and $\beta_1 = 1$, making it non-stationary. $\alpha \neq 0$ implies a random walk with drift. For us to analyze time series that are non-stationary we need to make the data stationary and a simple way of doing this is by differencing the model. Differencing is just subtracting Y_{t-1} from Y_t (Y_t - Y_{t-1}). By doing this the process loses one observation. This is visualized in figure 4.1 where we see the graph for smoked fresh salmon and smoked fresh salmon first differenced, where the data has gone from non-stationary to stationary when first differenced.

Figure 4.1: Graph of variable transformed



A commonly used tool to check for unit root is the augmented Dickey-Fuller(ADF) test(Dickey & Fuller, 1979). The ADF test allows us to test for unit roots even if there is autocorrelation. The null hypothesis for the ADF-test is that there is a unit root, and the alternate hypothesis is that the time series is stationary. With the ADF-test we can include factors such as there being a constant, trend or constant and trend together.

$$\Delta Y_t = \alpha + \delta Y_{t-1} + \sum_{i=1}^{p} \beta_i \Delta Y_{t-i} + \gamma t + \varepsilon_t \tag{4.4}$$

The ADF equation contains in this case a constant α and a trend γ. As mentioned earlier the null hypothesis is that there is a unit root. In other words the time series is non-stationary. For the equation to be non-stationary or have a unit root the β needs to be equal to 1. We therefore test if $\delta = 0$. Before doing the ADF-test we need to know the amount of periods that will be used in the test. The lag length can be found in several ways. One way is to do the ADF test with different lagged periods starting with a large number until the results are statistically significant. In our case we take use of the Akaike information criteria(AIC) (Akaike. H, 1973).

$$AIC = -2\left(\frac{LL}{T}\right) + \frac{2t_p}{T} \tag{4.5}$$

Where LL is the log likelihood t_p is the total amount of parameters in the model and T is time. The AIC test calculates the optimal number of lags used in the ADF test.

4.2 Cointegration

Cointegration is in simple terms a long term relationship between two variables in time series data. For simplicity we can see this on a graph comparing two variables that are expected to have a long term relationship. In mathematical terms cointegration occurs when two variables X_t and Y_t are both integrated of order one I(1)(non-stationary) and by multiplying one of the variables with a constant θ that makes it integrated of order 0 I(0)(stationary): Y_t-θX_t (Engle & Granger, 1987). For this thesis we are using the Johansen test (Johansen, 1988, 1991). This test allows for multivariate systems with non-stationary variables. The Johansen test follows an unrestricted vector autoregression in the levels of variables

$$X_t = \Pi_1 X_{t-1} + ... + \Pi_k X_{t-k} + \epsilon_t \tag{4.6}$$

Here X_t is a n x 1 vector. The Π_i is a n x n matrix of parameters. μ is a constant and ϵ_t is the normally distributed errors that are serially uncorrelated and but has the contemporaneos covariance matrix Ω. The equation (0.6) rewritten in error correction form is given by:

$$\Delta X_t = \Gamma_1 \Delta X_{t-1} + ... + \Gamma_{k-1} \Delta Xk - 1 + \Pi \Delta X_{t-k} + \epsilon_t \tag{4.7}$$

Where Γ_i = - I + Π_1 + ... + Π_i, i = 1, ... , k - 1 and Π = - I + Π_1 + ... + Π_k.

The rank of Π, r, tells us how many different linear combinations that exist for X_t that are stationary. If r = n, the variables are stationary, if r = 0, none of the variables are stationary. If r < n, there are r linear combinations of X_t that are stationary. When this is the case $\Pi = \alpha\ \beta$', where α and β are n x r matrices and β holds the cointegration vectors and α is the adjustment parameters.

The Johansen test uses two different tests for cointegration vectors: the trace test, and the maximum eigenvalue test, where both tests are likelihood-ratio tests. The null hypothesis for the trace test is that there are r cointegrating vectors against the alternative hypothesis that there are n cointegrating vectors.

$$J_{trace} = -T \sum_{i=r+1}^{n} ln(1 - \hat{\lambda}_i) \tag{4.8}$$

For the maximum eigenvalue test the null hypothesis of r cointegrating vectors against the alternative of r+1 cointegrating vectors.

$$J_{max} = -Tln(1 - \hat{\lambda}_{r+1}) \tag{4.9}$$

For bivariate cointegration test it is preferred to use the trace test. The trace test also shows durability against skewness and excess kurtosis in the error (Cheung & Lai, 1993).

The Johansen test can also be used to find exogeneity or price leadership (Johansen, 1988). Exogeneity means that the X variables does not depend on the dependent variable Y (Engle, R.F., Hendry, D.F., and Richard, J.F., 1983). This is in simpler terms if changes in export price lead to changes in retail price, or if changes in retail price leads to changes in export price. It is safe to. To analyze for price leadership we use weak exogeneity test in a VAR framework.

By using the Johansen test we also get the option to test the "law of on price" (LOP). In a market integration context the LOP gives us indication of if the markets are perfectly integrated. In our case with price transmission analysis it tells us if the price transmission is complete or not. To test for LOP we have to add some restrictions to the variables.

$$\begin{bmatrix} \Delta p_t^1 \\ \Delta p_t^2 \end{bmatrix} = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} \begin{bmatrix} b_1 & b_2 \end{bmatrix} \begin{bmatrix} p_{t-1}^1 \\ p_{t-1}^2 \end{bmatrix} \tag{4.10}$$

Here we have a system of two variables p_1 and p_2. We assume that the prices are non-stationary, cointegrated, one lag and no error term in the system. If b_1 = -b_2 then the

LOP hold or in other words there is complete price transmission (Asche et al. 2014). Here b_1 is set to be 1 and so b_2 is set to be -1 and calculated with these restrictions.

4.3 Vector Error Correction Model

The vector error correction model gives us the opportunity to conduct the Johansen test for the error corrected model as well as gives us better estimates for the price transmission elasitcities β. The VECM is based on a VAR model with p lags, rewritten as:

$$\Delta Y_t = \alpha(\beta Y_{t-1} + \mu + \rho t) + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-1} + \gamma + \tau t + \varepsilon_t \tag{4.11}$$

In equation 4.11 the option to have a time trend and a constant is available. In our case we estimate the VECM using a restricted time trend. This means that we assume the time trend to be linear and not quadratic. By adding this restriction we allow the equations to be trend stationary. For equation 4.11 to be assumed trend stationary, τ must be equal to 0.

By using the VECM we are able to compare the β from normal regression vs. with VECM to see more accurate β for the variables. The results and comparison will be conducted in the next two sections.

5 Empirical Results

In this section i will go through the results from the analyses for Germany and Spain conducted on stata.

5.1 Empirical results for Germany

In this section I am going through the empirical results of the analyses that are done, for the price transmission from export price to retail prices in Germany. The analyses are done on Stata.

5.1.1 Descriptive statistics Germany

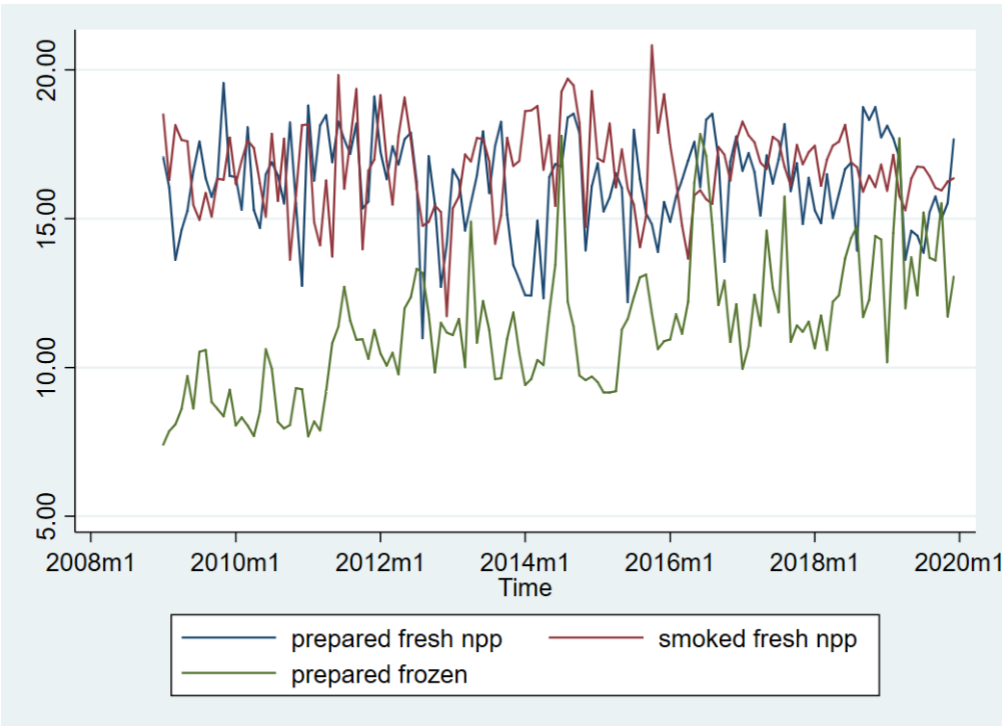
Table 5.1 contains all data provided for German retail market. I have included the descriptive statistics for all of the data because it gives us a better understanding of the market. I will, however, not use all of the data in the price transmission analyses. There are 132 periods observation for all of the variables. Included in the table is amount of observations, mean, standard deviation, minimum value, maximum value and coefficient of variation(CV). The CV gives us an indication of the volatility in the price.

Table 5.1: Descriptive statistics for Germany

Variable	n	Mean	Std.Dev	Min	Max	CV
Export:						
Germany Export	132	3.94	1.18	2.02	6.37	0.30
Retail:						
Natural fresh PP	132	12.95	2.39	7.37	18.82	0.18
Natural fresh NPP	132	18.64	3.08	13.24	24.52	0.17
Natural fresh	132	16.02	2.06	9.06	19.34	0.13
Natural frozen	132	12.44	1.74	9.67	17.11	0.14
Prepared fresh NPP	132	16.18	1.66	10.99	19.56	0.10
Prepared fresh PP	132	15.99	3.73	9.09	24.58	0.23
Prepared fresh	132	16.15	2.84	10.40	23.46	0.18
Prepared frozen	132	11.30	2.24	7.41	17.86	0.20
Smoked fresh NPP	132	16.72	1.46	11.73	20.82	0.09
Smoked fresh PP	132	18.24	2.92	13.83	23.99	0.16
Smoked fresh	132	18.11	2.70	14.01	23.58	0.15
Smoked frozen	132	41.87	17.61	0.00	78.75	0.42
Fresh total	132	18.19	2.75	14.01	23.91	0.15
Frozen total	132	17.39	2.18	14.03	22.27	0.13
Smoked total	132	12.37	1.84	9.39	17.22	0.15
Salmon total	132	15.70	2.15	12.15	20.07	0.14

From table 5.1 we can see the variations in price mean. There are large variations in the mean price of the different products. The lowest mean price for the retail market is prepared frozen salmon, while the highest is for smoked frozen salmon. The mean price is expected for smoked salmon, but it was expected that natural salmon would have the lowest mean price. This is because of earlier mentioned reason of value added to the products. Smoked frozen salmon data has very high price compared to other smoked salmon prices, because of the volume sold being much lower than the other products. The numbers for smoked frozen are generally not a good representation of how the price would act in an established market. This variable is therefore omitted in the price transmission analysis. There is some indication of a pattern in the PP vs. NPP. For natural salmon PP has a lower mean price than the NPP natural salmon. It is similar for prepared salmon, where PP has a lower mean price than NPP. However, for smoked salmon the PP smoked salmon has a higher price than NPP smoked salmon.

Figure 5.1: Graph of mean-reverting data



After going through the descriptive statistics, the next step is to carry out the ADF-test for all the variables. Before however we can see an indication of the output of the ADF-test by looking at figure 5.1. We see the values in table 5.2 that are mean-reverting. This is visible in prepared fresh NPP and smoked fresh NPP salmon. Prepared frozen salmon also looks mean-reverting after 2011. The variables are all in natural logarithmic form. The ADF-test was done for data with only a constant, in levels and with first difference. In addition the ADF-test was done with constant and a trend, in levels and with first difference. The lag length is in the parentheses next to the values from the ADF-test. As expected most of the data is non-stationary except for earlier mentioned variables; smoked fresh NPP, prepared fresh NPP, and prepared frozen. All of the variables are stationary with a constant at first difference. The ADF-test with trend also yields similar result where majority of the data is non-stationary in levels and stationary with first difference. But some variables behave different with the trend. In addition to the earlier mentioned stationary variables prepared fresh, prepared fresh PP, and natural fresh PP are also stationary with significance at 1%, 1%, and 5% respectively. This is also known as trend stationarity.The values that are non stationary are used in the price transmission analysis.

Table 5.2: ADF-test for Germany

Variable	Constant	Diff. Constant	Constant + Trend	Diff. Constant + Trend
Export:				
Germany Export	-1.535(2)	**-6.972(1)	-3.336(2)	**-6.938(1)
Retail:				
Smoked frozen	-1.383(3)	**-4.224(4)	-2.155(3)	*-4.067(4)
Smoked fresh PP	-0.959(2)	**-7.992(1)	-1.960(2)	**-7.963(1)
Smoked fresh NPP	**-6.415(1)	**-6.978(4)	**-6.414(1)	**-6.847(4)
Prepared frozen	*-3.485(2)	**-6.378(4)	**-5.137(2)	**-6.355(4)
Prepared fresh PP	-2.444(2)	**-7.612(2)	**-4.584(2)	**-7.583(2)
Prepared fresh NPP	**-4.351(3)	**-9.795(2)	**-4.359(3)	**-9.760(2)
Natural frozen	-2.072(3)	**-7.158(2)	1.957(3)	**-7.133(2)
Natural fresh PP	-1.734(4)	**-8.192(3)	*-3.638(4)	**-8.173(3)
Natural fresh NPP	-1.224(4)	**-6.401(4)	-2.722(4)	**-6.366(4)

5.1.2 Price transmission Germany

The price transmission analysis was conducted with the variables that were non-stationary without trend. Variables that were trend stationary are included in the analysis. The test is conducted with the retail prices being the dependent variable and the export price being the explanatory variable. The results for the Johansen test alongside LOP, weak exogeneity, and price transmission elasticities are reported in table 5.3.

The Johansen test results are all very similar to one another. All but three variables reject the null hypothesis of there being zero cointegrating vectors between the retail price and the export price. This indicates in our case in a bivariate cointegration test that there are no more than one cointegrating vectors between retail and export. The cointegration test has both trace and max test results. Both of the test yield similar results. From these test results we can say that there is a relationship between retail and export for all variables but the ones mentioned. There are no variables with more than one cointegrating vector.

Further a likelihood ratio test for law of one price(LOP) was conducted. Table 5.3 shows that the hypothesis of LOP is rejected for 6 of the variables. Smoked fresh NPP, Prepared frozen, Prepared fresh NPP, natural fresh PP, and natural fresh NPP are all statistically significant. Therefore the price transmission is incomplete from export to these variables. The rest of the variables do not reject the hypothesis of LOP and the price transmission is complete for these variables. However, we cannot conclude this for the values that do not have any cointegrating vectors.

Table 5.3: Johansen test for Germany

Variable	Rank	Trace test	Max test	LOP	Weak Exogeneity	Price (β) Transmission
Smoked fresh PP	$P = 0$	32.14	26.57	1.016	**17.30	0.4345
	$P \leq 1$	$\star$5.57	5.57		**6.81	(0.000)
Smoked fresh NPP	$P = 0$	70.36	63.47	**46.4	**12.70	0.0180
	$P \leq 1$	$\star$6.89	6.89		3.81	(0.482)
Prepared frozen	$P = 0$	36.97	28.21	**15.89	**7.50	0.2995
	$P \leq 1$	$\star$8.76	8.76		*3.95	(0.000)
Prepared fresh PP	$P = 0$	27.40	17.51	3.211	3.56	0.4857
	$P \leq 1$	$\star$9.89	9.89		**8.95	(0.000)
Prepared Fresh NPP	$P = 0$	75.80	68.21	**42.39	**27.31	-0.0040
	$P \leq 1$	$\star$7.59	7.59		1.81	(0.897)
Natural frozen	$P = 0$	$\star$18.51	14.59	2.442	**9.99	0.2787
	$P \leq 1$	3.91	3.91		3.60	(0.000)
Natural fresh PP	$P = 0$	27.92	16.90	*4.263	2.47	0.4387
	$P \leq 1$	$\star$11.01	11.01		**8.51	(0.000)
Natural fresh NPP	$P = 0$	80.55	72.26	**50.74	**16.48	0.4964
	$P \leq 1$	$\star$8.29	8.29		1.78	(0.000)

The next column in table 5.3 shows the results for the weak exogeneity test for the retail prices. The results show that more or less all variables are endogenous, except for prepared fresh NPP salmon. The price leader is not similar in every variable. For smoked salmon products except for the NPP products there is no clear price leader. there does not seem to be any clear direction of which price causes the other price to change. It seems that for NPP products and natural frozen salmon the price leader is the export price. While for the PP products there is no clear pattern as smoked fresh PP has no sign of a price leader while prepared fresh PP and natural fresh PP has the retail price as the price leader.

Finally we look at the price transmission elasticities given by β. These results tells us how large a change in the export price would reflect in the retail price. The elasticities are varied and span from β=-0.004 for prepared fresh NPP with the lowest reaction to β=0.4964 for natural fresh NPP with the highest reaction to export price changes. The β for natural frozen, which has no cointegrating vectors is 0.2787. This β should not be seen as "correct".

Table 5.4: VECM estimates for Germany

Variable	β	t	P-value
Smoked fresh PP	-0.6730	-5.76	0.000
Smoked fresh NPP	-0.0138	-0.23	0.815
Prepared frozen	0.2357	2.10	0.036
Prepared fresh PP	-0.2032	-1.08	0.286
Prepared Fresh NPP	-0.0557	-0.82	0.413
Natural frozen	8.7321	3.84	0.000
Natural fresh PP	-0.0228	-0.20	0.844
Natural fresh NPP	-0.3397	-9.77	0.000

Table 5.4 has the beta estimates from the VECM along with the t-stat and the p-value of the t-stat. Four out of eight variables are statistically significant. There is however a $\beta = 8.73$ which is very high. We use these to calculate for full price transmission between the retail variables and the export. Where the null is that there is full price transmission, with the alternative of there not being full price transmission. These can be seen in table 5.5.

Table 5.5: VECM cointegrating equations for Germany

Variable	test-statistic	P-value	Proportionality test
Smoked fresh PP	33.175	0.0000	-4.26 (0.0000)
Smoked fresh NPP	0.0548	0.8148	0.77 (0.4427)
Prepared frozen	4.4185	0.0356	-1.1 (0.2734)
Prepared fresh PP	1.1570	0.2821	-0.8 (0.9364)
Prepared Fresh NPP	0.6694	0.4133	0.18 (0.8574)
Natural frozen	14.713	0.0001	-2.84 (0.0052)
Natural fresh PP	0.0386	0.8442	0.8 (0.4252)
Natural fresh NPP	95.396	0.0000	-8.77 (0.0000)

In table 5.5 we have the results from performing a johansen test under a vector error correction model(VECM). Here the test results show us that there are 4 variables with one cointegrating equation. Smoked fresh PP, prepared frozen, natural frozen, and natural fresh NPP have all got one cointegrating equation while the rest does not. We will discuss the difference between the results from the VECM and the normal model in the next section. The proportionality test shows us which variables that have full price transmission. Our results show that four variables have full price transmission as the null hypothesis of there being full price transmission cannot be rejected.

5.2 Empirical results for Spain

In this section I am going through the empirical results of the analyses that are done, for the price transmission from export price to retail prices in Spain, similarly to the previous section.

5.2.1 Descriptive statistics Spain

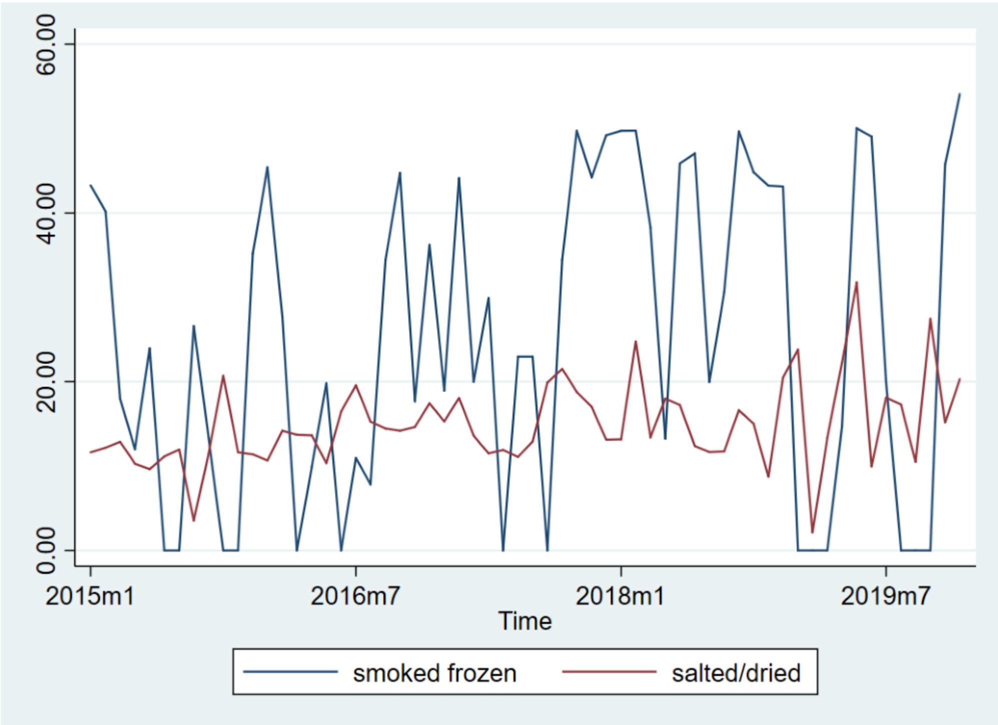
Table 5.4 consists of the same statistics measured for Spain as there were for Germany in table 5.1. The largest difference is the number of observations being reduced from 132 to 60. This was necessary to be able to get proper results as there were multiple variables with little or no data for the earlier years. 60 observations is equivalent of 5 years of data.The mean price for export is 4.98 with a standard deviation of 0.81. For retail the variable with the lowest mean price is natural fresh NPP salmon at 10.41, a standard deviation of 1.03 and a relatively low CV at 0.10. On the other side prepared fresh has the highest mean price of 29.24 with a standard deviation 4.42 and a CV of 0.15. These values seem to be stable for the time being, however, prepared salmon has had a large increase in price.

Table 5.6: Descriptive statistics for Germany

Variable	n	Mean	Std.Dev	Min	Max	CV
Export:						
Spain Export	60	4.98	0.81	3.23	6.30	0.16
Retail:						
Natural fresh NPP	60	10.41	1.03	8.17	12.08	0.10
Natural fresh PP	60	13.67	1.47	11.19	18.77	0.10
Natural fresh	60	11.00	1.03	8.77	12.98	0.09
Naturalfrozen	60	15.80	1.43	13.14	19.87	0.09
Prepared fresh	60	29.24	4.42	21.32	36.38	0.15
Prepared frozen	60	14.68	3.92	9.25	27.84	0.27
Prepared	60	23.47	4.06	15.54	30.31	0.17
Salted and/or Dried	60	14.87	5.12	2.12	31.76	0.34
Smoked fresh NPP	60	23.25	1.67	20.18	26.65	0.07
Smoked fresh PP	24	31.23	1.18	29.43	33.72	0.04
Smoked fresh	60	25.91	1.82	22.56	28.90	0.07
Smoked frozen	60	25.20	18.65	0	54.07	0.74
Smoked total	60	25.93	1.82	22.56	28.90	0.07
Frozen total	60	15.74	1.37	12.86	19.11	0.09
Fresh total	60	12.82	1.38	9.75	15.71	0.11

Most of the variables seem to be pretty stable and have expected and normal growth and price ranges. But two variables that stands out are smoked fresh NPP and Smoked frozen. These variables have extremely high CV at 0.95 for smoked fresh NPP and 0.74 for smoked frozen. The prices range from 0 to 33.72 and 0 to 54.07 giving them standard deviations fairly close to the mean prices. This is because of lack of data for earlier observations for these variables. For smoked fresh NPP i have decided to reduce amount of observations to 24 to calculate from the last 2 years of data. I have not done this for smoked frozen as the problem is gaps in the data unlike smokedfresh NPP.

Figure 5.2: Graph of mean-reverting data



The ADF-test results for Spain are uniform with our expectation of the behaviour. All but two variables are non-stationary with stationarity at first difference. The two variabels that are stationary are smoked frozen and salted and/or dried salmon. We can see the stationarity visually in figure 5.2. Here we can also see the gaps in the data for smoked frozen salmon. All of the data has identical results in test with and without trend. The lag value is reported in the parentheses next to the ADF-test values. The non-stationary variable are used in the price transmission analysis for Spain.

Table 5.7: ADF-test for Spain

Variable	Constant	Diff. Constant	Constant + Trend	Diff. Constant + Trend
Export:				
Spain Export	-2.205(2)	**-4.937(2)	-2.313(2)	**-4.996(2)
Retail:				
Smoked frozen	**-4.979(0)	**-5.957(2)	**-5.976(0)	**-5.736(2)
Smoked fresh PP	-1.928(2)	**-5.494(2)	-2.259(2)	**-5.421(2)
Smoked fresh NPP	-1.874(2)	**-4.484(4)	-2.675(2)	**-4.536(4)
Salted and/or dried	**-7.390(0)	**-5.651(4)	**-7.821(0)	**-5.592(4)
Prepared frozen	-1.738(4)	**-5.338(3)	-1.389(4)	**-5.502(3)
Prepared fresh	-1.170(1)	**-7.772(0)	-2.423(1)	**-7.693(0)
Natural frozen	-1.219(2)	**-4.348(4)	-3.331(2)	**-4.306(4)
Natural fresh PP	-1.355(4)	**-5.078(4)	-2.485(4)	**-5.067(4)
Natural fresh NPP	-2.217(2)	**-4.498(1)	-2.013(2)	**-4.570(1)

5.2.2 Price transmission analysis Spain

The price transmission analysis for Spain was done in the exact same way as it was for Spain. The analysis for Spain was done for 5 years while it was 11 years for Germany. The main difference was the variable for smoked fresh pp which was done over 2 years as opposed to 5 years for the rest of the analysis. The analysis are done with the retail variable as a dependent variable to the export price. In table 5.6 we have the results of the different analyses conducted.

The Johansen test results for Spain are as uniform as in the analysis for Germany, but there is a majority of variables with no cointegrating vectors. Smoked fresh NPP and Prepared fresh salmon both have 1 cointegrating vector. Both the trace- and max-test have the same concluding results for all the variables. From these results we can see that there is a relationship between smoked fresh NPP and export price, and prepared fresh and export price.

Next test was the likelihood ratio test for LOP. Four out of seven variables reject the hypothesis of LOP. Smoked fresh PP and natural frozen are statistically significant at the 5% level while smoked fresh NPP and natural fresh PP are statistically significant at the 1% level.

Table 5.8: Johansen test for Spain

Variable	Rank	Trace test	Max test	LOP	Weak Exogeneity	Price (β) transmission
Smoked fresh PP	P = 0	⋆18.95	11.94	*5.359	0.62	0.0305
	P ≤ 1	7.01	7.01		**11.16	(0.123)
Smoked fresh NPP	P = 0	28.12	21.88	**10.39	1.59	0.2884
	P ≤ 1	⋆6.24	6.24		**8.91	(0.000)
Prepared frozen	P = 0	⋆18.87	11.82	0.2045	**9.36	0.6380
	P ≤ 1	7.04	7.04		1.86	(0.000)
Prepared fresh	P = 0	27.52	22.47	1.272	**16.17	0.5594
	P ≤ 1	⋆5.05	5.05		**8.28	(0.000)
Natural frozen	P = 0	⋆21.20	14.55	*5.218	0.60	0.2345
	P ≤ 1	6.65	6.65		**8.44	(0.000)
Natural fresh PP	P = 0	⋆21.66	16.51	**9.185	2.32	0.2760
	P ≤ 1	5.14	5.14		*5.54	(0.000)
Natural fresh NPP	P = 0	⋆19.53	12.34	2.493	1.25	0.5321
	P ≤ 1	7.19	7.19		3.44	(0.000)

Of the retail variables only two variables are endogenous. Prepared frozen and prepared fresh salmon are endogenous while the rest of the retail prices are exogenous. This gives us the implication that the retail price is the price leader for many of the variables. For prepared fresh salmon both retail and export price are endogenous, making it difficult to say for sure if there is a price leader in this instance. The same goes for natural fresh NPP salmon, but in this case both prices are exogenous with the same conclusion that we cannot see a clear price leader or a sign of it.

For the Spanish market the price transmission elasticites (β) range from 0.0305 at the lowest and 0.6380 at the highest, for smoked fresh PP and prepared frozen respectively. However, these values should not be taken as very accurate because the variables are not cointegrated with the export price. For the cointegrated variables the price transmission is a little more relevant. The β for smoked fresh NPP is 0.2884 and the β for prepared fresh is 0.5594.

Table 5.9: VECM estimates for Spain

Variable	β	t	P-value
Smoked fresh PP	-0.1043	-1.41	0.160
Smoked fresh NPP	-0.2720	-5.25	0.000
Prepared frozen	-1.2861	-3.20	0.001
Prepared fresh	-0.6965	-4.92	0.000
Natural frozen	-0.1163	-1.45	0.148
Natural fresh PP	-0.0941	-1.27	0.206
Natural fresh NPP	-0.6897	-13.13	0.000

Table 5.9 similarly to table 5.5 shows the estimated betas along with t-stat and p-value for the variables in VECM. Out of seven variables four of them are statistically significant. One variable that stands out is the β for prepared frozen salmon with elasticity 1.286. The elasticities from VECM will be compared to the other elasticities.

Table 5.10: VECM cointegrating equations for Spain

Variable	test-statistic	P-value	Proportionality test
Smoked fresh PP	1.9749	0.1599	-0.41 (0.6847)
Smoked fresh NPP	27.560	0.0000	-4.25 (0.0000)
Prepared frozen	10.236	0.0014	-2.2 (0.0318)
Prepared fresh	24.241	0.0000	-3.92 (0.0002)
Natural frozen	2.0904	0.1482	-0.45 (0.6544)
Natural fresh PP	1.6028	0.2055	-0.27 (0.7881)
Natural fresh NPP	172.29	0.0000	-12.13 (0.0000)

In table 5.10 are the results from the cointegration test in the VECM. The results show four variables with a cointegrating equation. Smoked fresh NPP, prepared frozen, prepared fresh, and natural fresh NPP have all got cointegrating equations. The difference in results from the VECM. The proportionality test results gives us an indication of there being full price tranmission or not. For Spain there are three variables that can be considered to have full price transmission. These variables are smoked fresh PP, natural frozen, and natural fresh PP. The other variables fail to reject the null hypothesis of there being full price transmission. Cointegration test and the previous test will be discussed in the discussion section of the thesis.

6 Discussion

In this section i will discuss the empirical results from the analyses and tie them in to the economic theory.

From our results in the analyses for Germany we can see that there is a clear pattern in the price transmission elasticities. The elasticities for the frozen salmon is close to 0.3 with prepared frozen being 0.29 and natural frozen 0.27. This is lower than the fresh salmon products which all are around 0.43-0.49. A lower elasticity for the frozen products makes sense economically. In the price theory section of the thesis we went through the possibility of a product having several steps between the export and the retail products. This was factors such as preparation, packaging and storing. In this case we can see that the products which are easier to store over time are subject to a lower degree of price transmission from the export prices. When the export price changes, but already bought salmon is stored then the price change will not impact in the same way as if there was no extra steps between export and retail. In our case even though the results make sense from en economic perspective we cannot trust these numbers completely. If we look at the results we can see that the natural fresh salmon is not cointegrated with the export price, we can therefore not trust this result.

For the Spanish market the pattern is not as clear as in the German market. There is however also less variables that are cointegrated making some of the betas less reliable in the case of price transmission. We can only look at the two cointegrated variables as reliable results. Here smoked fresh NPP salmon has a beta of 0.29 and prepared fresh salmon has beta of 0.56. This is in line with the theory. The product that is easier stored has the lower price transmission elasticity, similarly to the German market. If we disregard the results from the Johansen test and only look at the price transmission elasticities the results show that the price transmission is lowest for frozen products and at similar level for fresh products.

Between the PP and NPP products the elasticity is higher for NPP products. This can be seen for natural fresh salmon in the German and Spanish market. In our results there are some variables with insignificant betas making the results void.

The output from the VECM estimation gives us comparable results to that of the Johansen test and the regression betas. Comparing the cointegration tests from the VECM and earlier model we get different results. For some of the variables the different models yield the same results for the cointegration test. There are however some variables that get different results. For the German market, smoked fresh NPP, prepared fresh PP, prepared fresh NPP, and natural fresh PP all go from having one cointegrating factor to none in VECM. Natural frozen acts in the opposite way going from not having any cointegrating vectors to having one in VECM. In the Spanish market the VECM has more variables with one cointegrating vector. Prepared frozen and natural frozen NPP both have one cointegrating vector in VECM compared to none before. The rest of the variables yield the same results for both markets.

The β from the VECM are also comparable with the regressed β, but with the results from the VECM giving more appropriate results. In the German market the results show no clear sign of the price tranmission being highest for natural products or lowest for the storable and prepared products. Looking at the statistically significant β for smoked fresh PP is 0.6730 vs. the previous $\beta = 0.4345$. For preparedfrozen the VECM $\beta = 0.2357$ vs. previous $\beta = 0.2995$. Finally for natural fresh NPP the $\beta = 0.3397$ vs. previous $\beta = 0.4964$. For the Spanish market the results are similar with no clear sign of the price transmission decreasing with higher processing. Looking at the statistically significant β for the variables. For smoked fresh NPP the VECM $\beta = 0.2720$ vs. previously $\beta = 0.2884$. Prepared fresh having VECM $\beta = 0.6965$ vs. previously $\beta = 0.5594$. Finally for natural fresh NPP the VECM $\beta = 0.6897$ vs. previously $\beta = 0.5321$. Both the German and Spanish results have some unrealistic results. For the German market the VECM statistically significant β for natural frozen salmon is 8.732. In this case it is better to rely on the regression $\beta = 0.278$. The odd result is not as unrealistic as the one for Germany. The VECM β is 1.286 for prepared frozen salmon while being 0.638 for the regression. For this result as for the one for Germany it is better to rely on the regression coefficient. From these values the β coefficients fail to show the expected decrease in price transmission with increase in processing of the product. This can be for reasons such as transport costs. For salmon products that are not processed and cannot be stored the transport cost may be the reason for the low price transmission elasticities. Being the major part of the marketing margin may explain the deviation from our expectations going in to the study. Other reasons can be exchange rates affecting the market prices by changing the relative prices(Tveterås & Asche, 2008).

7 Conclusion

In this thesis i have performed a price transmission analysis for the German and Spanish salmon market. The study was done with different product categories to get a better understanding of how the price reacts for the different parts of the salmon market. The analyses were done for monthly data for both countries markets. For Germany there was used 11 years of data for Spain there was used 5 years of data and less for one variable. This was to get most accurate results as there were variables with no data for much of the time. The analysis was done with a econometric framework. Tests such as augmented dickey fuller test, johansen test, and VECM estimation were used. Additionally the LOP, weak exogeneity and proportionality was tested for the variables. The combination of these tests showed us if there is price transmission and the extent.

The study shows that there is price transmission for some of the products studied. There is however, not any sign of there being increasing nor decreasing price transmission relative to the processing of the product. For the German market there is some indication of the frozen products having lower price transmission than the fresh. While there being no sign of it for the Spanish market. This is if we disregard the cointegration test. The price transmission differed for each product type. Our assumptions going in to the thesis was that there would be clear signs of high price transmission for products with little to no processing and low for products with more steps between consumer and export. The results as mentioned did not give us a clear sign of this.

The Exogeneity tests showed us the price leadership. This showed that there is variations in these subsections of the salmon market. This shows that the salmon market is very varied and to only look at salmon as a whole does not give a good indication of how the market acts. The weak exogeneity test shows us that NPP salmon is the price leader in relation to the export. This means that the export price reacts to the NPP price rather than the other way. For PP salmon products it is the opposite where the export price is the price leader and the PP price reacts to changes in export.

Testing the LOP and proportionality also showed a complete price transmission or not.

These are econometrically similar, but our focus was on the VECM. The proportionality test showed that the price transmission was complete for only one of the variables in the VECM. This shows us that a price increase only parts of the price increase goes to the consumer. Reasons for this can be change in the marketing margin e.g. smaller portions or added accessories.

Further studies should be conducted around this subject for these countries. For the Spanish market the data is inadequate for longer periods for many of the products. For the German market further studies can examine any changes in the markets and conduct further studies in the market.

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Appendix

GERMANY

1 . varsoc lGermanyExport

Selection-order criteria
Sample: **2009m5 - 2019m12** Number of obs = **128**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-27.8762				.091934	.45119	.460244	.473472
1	148.982	353.72*	1	0.000	.00589	-2.2966	-2.27849	-2.25204*
2	150.815	3.6652	1	0.056	.005814*	-2.30961*	-2.28245*	-2.24277
3	150.911	.19214	1	0.661	.005897	-2.29549	-2.25927	-2.20636
4	151.526	1.2299	1	0.267	.005933	-2.28947	-2.2442	-2.17806

Endogenous: lGermanyExport
Exogenous: _cons

2 . varsoc lsmokedfrozen

Selection-order criteria
Sample: **2010m3 - 2019m12, but with gaps** Number of obs = **75**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	46.4476				.017426	-1.21194	-1.1996	-1.18104
1	77.2496	61.604	1	0.000	.007871	-2.00666	-1.98198	-1.94486
2	92.7665	31.034*	1	0.000	.005345	-2.39377	-2.35676*	-2.30107*
3	93.9886	2.4442	1	0.118	.005314*	-2.3997*	-2.35034	-2.2761
4	94.2293	.48137	1	0.488	.005423	-2.37945	-2.31776	-2.22495

Endogenous: lsmokedfrozen
Exogenous: _cons

3 . varsoc lsmokedfreshpp

Selection-order criteria
Sample: **2009m5 - 2019m12** Number of obs = **128**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	59.7058				.023397	-.917277	-.908224	-.894996
1	290.904	462.4	1	0.000	.000641	-4.51412	-4.49601	-4.46956*
2	292.954	4.1008*	1	0.043	.000631*	-4.53053*	-4.50337*	-4.46369
3	293.301	.69455	1	0.405	.000637	-4.52033	-4.48412	-4.43121
4	293.484	.36512	1	0.546	.000646	-4.50756	-4.46229	-4.39615

Endogenous: lsmokedfreshpp
Exogenous: _cons

4 . varsoc lsmokedfreshnpp

Selection-order criteria
Sample: **2009m5 - 2019m12** Number of obs = **128**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	128.234				.008019	-1.98804	-1.97898	-1.96576
1	132.351	8.2342*	1	0.004	.007638*	-2.03674*	-2.01863*	-1.99218*
2	132.629	.55513	1	0.456	.007725	-2.02545	-1.99829	-1.95861
3	133.092	.92533	1	0.336	.00779	-2.01706	-1.98084	-1.92793
4	133.152	.12059	1	0.728	.007905	-2.00237	-1.95711	-1.89097

Endogenous: lsmokedfreshnpp
Exogenous: _cons

5 . varsoc lpreparedfrozen

Selection-order criteria
Sample: **2009m5 - 2019m12** Number of obs = **128**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	33.0462				.035487	-.500722	-.491668	-.47844
1	77.4498	88.807	1	0.000	.018011	-1.1789	-1.1608	-1.13434*
2	79.5818	4.2641*	1	0.039	.017695*	-1.19659*	-1.16943*	-1.12975
3	79.6424	.12106	1	0.728	.017957	-1.18191	-1.1457	-1.09279
4	79.6513	.01798	1	0.893	.018238	-1.16643	-1.12116	-1.05502

Endogenous: lpreparedfrozen
Exogenous: _cons

6 . varsoc lpreparedfreshpp

Selection-order criteria
Sample: **2009m5 - 2019m12** Number of obs = **128**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	5.82138				.054301	-.075334	-.066281	-.053053
1	72.1903	132.74	1	0.000	.019554	-1.09672	-1.07862	-1.05216*
2	74.3084	4.2361*	1	0.040	.019215*	-1.11419*	-1.08703*	-1.04735
3	74.6764	.73614	1	0.391	.019406	-1.10432	-1.06811	-1.01519
4	74.7799	.20701	1	0.649	.01968	-1.09031	-1.04505	-.978904

Endogenous: lpreparedfreshpp
Exogenous: _cons

7 . varsoc lpreparedfreshnpp

Selection-order criteria
Sample: **2009m5 - 2019m12** Number of obs = **128**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	104.677				.011587	-1.61996	-1.6109	-1.59768
1	109.89	10.426	1	0.001	.010849	-1.68578	-1.66768*	-1.64122*
2	110.199	.61842	1	0.432	.010967	-1.67499	-1.64783	-1.60814
3	112.537	4.6755*	1	0.031	.01074*	-1.69589*	-1.65968	-1.60677
4	112.599	.12436	1	0.724	.010899	-1.68124	-1.63597	-1.56983

Endogenous: lpreparedfreshnpp
Exogenous: _cons

8 . varsoc lnaturalfrozen

Selection-order criteria
Sample: **2009m5 - 2019m12** Number of obs = **128**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	79.8174				.017088	-1.23152	-1.22247	-1.20924
1	233.376	307.12	1	0.000	.001576	-3.61525	-3.59714	-3.57068
2	236.841	6.9307	1	0.008	.001516	-3.65377	-3.62661	-3.58692*
3	238.971	4.2597*	1	0.039	.00149*	-3.67142*	-3.63521*	-3.5823
4	239.435	.92834	1	0.335	.001502	-3.66305	-3.61778	-3.55164

Endogenous: lnaturalfrozen
Exogenous: _cons

9 . varsoc lnaturalfreshpp

Selection-order criteria
Sample: **2009m5 - 2019m12** Number of obs = **128**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	30.3146				.037034	-.458041	-.448988	-.435759
1	81.9276	103.23	1	0.000	.016794	-1.24887	-1.23076	-1.20431
2	89.0014	14.148	1	0.000	.015273	-1.34377	-1.31661	-1.27693
3	101.163	24.323*	1	0.000	.012829	-1.51817	-1.48196*	-1.42905*
4	102.233	2.1399	1	0.144	.012815*	-1.51927*	-1.474	-1.40786

Endogenous: lnaturalfreshpp
Exogenous: _cons

10 . varsoc lnaturalfreshnpp

Selection-order criteria
Sample: **2009m5 - 2019m12** Number of obs = **128**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	52.2697				.02628	-.801089	-.792036	-.778807
1	167.033	229.53	1	0.000	.004443	-2.57864	-2.56053	-2.53408
2	171.884	9.7023	1	0.002	.004183	-2.63881	-2.61165	-2.57197*
3	174.098	4.4287*	1	0.035	.004105	-2.65779	-2.62157	-2.56866
4	175.737	3.2775	1	0.070	.004064*	-2.66777*	-2.6225*	-2.55636

Endogenous: lnaturalfreshnpp
Exogenous: _cons

11 .

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1 . varsoc d.lGermanyExport

Selection-order criteria
Sample: **2009m6 - 2019m12**   Number of obs   =   **127**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**147.462**				**.005832**	**-2.30649**	**-2.29739***	**-2.28409***
1	**148.898**	**2.8711**	**1**	**0.090**	**.005792***	**-2.31335***	**-2.29515**	**-2.26856**
2	**148.917**	**.03778**	**1**	**0.846**	**.005883**	**-2.2979**	**-2.2706**	**-2.23071**
3	**149.686**	**1.5385**	**1**	**0.215**	**.005904**	**-2.29426**	**-2.25787**	**-2.20468**
4	**149.973**	**.57349**	**1**	**0.449**	**.005971**	**-2.28303**	**-2.23754**	**-2.17106**

Endogenous: D.lGermanyExport
Exogenous: _cons

2 . varsoc d.lsmokedfrozen

Selection-order criteria
Sample: **2010m4 - 2019m12, but with gaps**   Number of obs   =   **69**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**63.0504**				**.009692**	**-1.79856**	**-1.78572**	**-1.76618**
1	**83.1293**	**40.158**	**1**	**0.000**	**.005575**	**-2.35157**	**-2.32588**	**-2.28682**
2	**84.4034**	**2.5482**	**1**	**0.110**	**.005531**	**-2.35952**	**-2.32098**	**-2.26238**
3	**84.5079**	**.20894**	**1**	**0.648**	**.005677**	**-2.33356**	**-2.28218**	**-2.20405**
4	**93.2184**	**17.421***	**1**	**0.000**	**.004541***	**-2.55706***	**-2.49283***	**-2.39516***

Endogenous: D.lsmokedfrozen
Exogenous: _cons

3 . d.varsoc lsmokedfreshpp
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4 . varsoc d.lsmokedfreshpp

Selection-order criteria
Sample: **2009m6 - 2019m12**   Number of obs   =   **127**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**287.506**				**.000643**	**-4.51191**	**-4.50281**	**-4.48951***
1	**289.615**	**4.218***	**1**	**0.040**	**.000632***	**-4.52937***	**-4.51117***	**-4.48458**
2	**289.924**	**.6189**	**1**	**0.431**	**.000639**	**-4.5185**	**-4.4912**	**-4.45131**
3	**290.078**	**.30744**	**1**	**0.579**	**.000647**	**-4.50517**	**-4.46877**	**-4.41559**
4	**290.149**	**.14237**	**1**	**0.706**	**.000657**	**-4.49054**	**-4.44505**	**-4.37857**

Endogenous: D.lsmokedfreshpp
Exogenous: _cons

5 . varsoc d.lsmokedfreshnpp

Selection-order criteria
Sample: **2009m6 - 2019m12**   Number of obs   =   **127**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**100.852**				**.012151**	**-1.57247**	**-1.56337**	**-1.55007**
1	**112.861**	**24.018**	**1**	**0.000**	**.010217**	**-1.74584**	**-1.72764**	**-1.70105**
2	**115.074**	**4.426**	**1**	**0.035**	**.010024**	**-1.76494**	**-1.73764**	**-1.69775**
3	**117.716**	**5.2858**	**1**	**0.021**	**.009768**	**-1.79081**	**-1.75442**	**-1.70123**
4	**122.827**	**10.22***	**1**	**0.001**	**.009156***	**-1.85554***	**-1.81004***	**-1.74356***

Endogenous: D.lsmokedfreshnpp
Exogenous: _cons

6 . varsoc d.lpreparedfrozen

Selection-order criteria
Sample: **2009m6 - 2019m12** Number of obs = **127**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	66.3185				.020931	-1.02864	-1.01954	-1.00624
1	72.3536	12.07	1	0.001	.019336	-1.10793	-1.08973*	-1.06314*
2	73.3089	1.9107	1	0.167	.019349	-1.10723	-1.07993	-1.04004
3	73.6113	.60482	1	0.437	.019563	-1.09624	-1.05985	-1.00666
4	75.5361	3.8495*	1	0.050	.019281*	-1.1108*	-1.06531	-.998828

Endogenous: D.lpreparedfrozen
Exogenous: _cons

7 . varsoc d.lpreparedfreshpp

Selection-order criteria
Sample: **2009m6 - 2019m12** Number of obs = **127**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	66.2463				.020955	-1.0275	-1.0184	-1.00511
1	71.1417	9.7908*	1	0.002	.019708	-1.08885	-1.07065*	-1.04406*
2	72.4532	2.6229	1	0.105	.019612*	-1.09375*	-1.06645	-1.02657
3	72.4753	.04424	1	0.833	.019916	-1.07835	-1.04196	-.988771
4	72.7177	.48471	1	0.486	.020156	-1.06642	-1.02093	-.954444

Endogenous: D.lpreparedfreshpp
Exogenous: _cons

8 . varsoc d.lpreparedfreshnpp

Selection-order criteria
Sample: **2009m6 - 2019m12** Number of obs = **127**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	80.2165				.016817	-1.2475	-1.2384	-1.22511
1	91.3796	22.326	1	0.000	.01433	-1.40755	-1.38936	-1.36276
2	101.29	19.82*	1	0.000	.012454*	-1.54787*	-1.52057*	-1.48068*
3	102.131	1.6834	1	0.194	.012485	-1.54537	-1.50898	-1.45579
4	102.161	.05969	1	0.807	.012677	-1.5301	-1.4846	-1.41812

Endogenous: D.lpreparedfreshnpp
Exogenous: _cons

9 . varsoc d.lnaturalfrozen

Selection-order criteria
Sample: **2009m6 - 2019m12** Number of obs = **127**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	229.723				.001597	-3.60193	-3.59284	-3.57954
1	233.802	8.1586	1	0.004	.001521	-3.65043	-3.63223	-3.60564*
2	236.208	4.8126*	1	0.028	.001488*	-3.67257*	-3.64528*	-3.60539
3	236.563	.70977	1	0.400	.001503	-3.66241	-3.62602	-3.57283
4	236.583	.03957	1	0.842	.001526	-3.64698	-3.60148	-3.535

Endogenous: D.lnaturalfrozen
Exogenous: _cons

10 . varsoc d.lnaturalfreshpp

Selection-order criteria
Sample: **2009m6 - 2019m12**   Number of obs   =   **127**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**71.7722**				**.019209**	**-1.11452**	**-1.10542**	**-1.09213**
1	**83.6304**	**23.716**	**1**	**0.000**	**.016189**	**-1.28552**	**-1.26732**	**-1.24073**
2	**97.8401**	**28.419***	**1**	**0.000**	**.013149**	**-1.49355**	**-1.46625***	**-1.42636***
3	**99.2488**	**2.8172**	**1**	**0.093**	**.013065***	**-1.49998***	**-1.46358**	**-1.4104**
4	**99.663**	**.82858**	**1**	**0.363**	**.013186**	**-1.49076**	**-1.44526**	**-1.37878**

Endogenous: D.lnaturalfreshpp
Exogenous: _cons

11 . varsoc d.lnaturalfreshnpp

Selection-order criteria
Sample: **2009m6 - 2019m12**   Number of obs   =   **127**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**163.572**				**.004525**	**-2.56019**	**-2.55109**	**-2.5378**
1	**169.466**	**11.788**	**1**	**0.001**	**.00419**	**-2.63726**	**-2.61907**	**-2.59247***
2	**171.662**	**4.3911***	**1**	**0.036**	**.004112**	**-2.65609**	**-2.6288**	**-2.58891**
3	**173.565**	**3.8061**	**1**	**0.051**	**.004054**	**-2.67031**	**-2.63392***	**-2.58073**
4	**175.013**	**2.896**	**1**	**0.089**	**.004025***	**-2.67737***	**-2.63187**	**-2.56539**

Endogenous: D.lnaturalfreshnpp
Exogenous: _cons

12 .

```
  ___  ____  ____  ____  ____(R)
 /__    /   ____/   /   ____/
___/   /   /___/   /   /___/
  Statistics/Data Analysis
```

User: 1

```
1 . dfuller lGermanyExport, lags(2)
```

Augmented Dickey-Fuller test for unit root Number of obs = **129**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-1.535**	**-3.500**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.5162**

```
2 . dfuller lsmokedfrozen, lags(3)
```

Augmented Dickey-Fuller test for unit root Number of obs = **75**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-1.383**	**-3.545**	**-2.910**	**-2.590**

MacKinnon approximate p-value for Z(t) = **0.5903**

```
3 . dfuller lsmokedfreshpp, lags(2)
```

Augmented Dickey-Fuller test for unit root Number of obs = **129**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-0.959**	**-3.500**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.7678**

```
4 . dfuller lsmokedfreshnpp, lags(1)
```

Augmented Dickey-Fuller test for unit root Number of obs = **130**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-6.415**	**-3.500**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.0000**

```
5 . dfuller lpreparedfrozen, lags(2)
```

Augmented Dickey-Fuller test for unit root Number of obs = **129**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-3.485**	**-3.500**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.0084**

```
6 . dfuller lpreparedfreshpp, lags(2)
```

Augmented Dickey-Fuller test for unit root Number of obs = **129**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-2.444**	**-3.500**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.1298**

7 . dfuller lpreparedfreshnpp, lags(3)

Augmented Dickey-Fuller test for unit root Number of obs = **128**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-4.351**	**-3.501**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.0004**

8 . dfuller lnaturalfrozen, lags(3)

Augmented Dickey-Fuller test for unit root Number of obs = **128**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-1.000**	**-3.501**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.7534**

9 . dfuller lnaturalfreshpp, lags(4)

Augmented Dickey-Fuller test for unit root Number of obs = **127**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-1.734**	**-3.501**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.4135**

10 . dfuller lnaturalfreshnpp, lags(4)

Augmented Dickey-Fuller test for unit root Number of obs = **127**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-1.224**	**-3.501**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.6634**

11 .

```
  ___  ____  ____  ____  ____(R)
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___/   /   /___/   /   /___/
  Statistics/Data Analysis

     User: 1
```

1 . dfuller lGermanyExport, trend lags(2)

Augmented Dickey-Fuller test for unit root Number of obs = **129**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-3.336**	**-4.030**	**-3.446**	**-3.146**

MacKinnon approximate p-value for Z(t) = **0.0605**

2 . dfuller lsmokedfrozen, trend lags(3)

Augmented Dickey-Fuller test for unit root Number of obs = **75**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-2.155**	**-4.095**	**-3.475**	**-3.165**

MacKinnon approximate p-value for Z(t) = **0.5153**

3 . dfuller lsmokedfreshpp, trend lags(2)

Augmented Dickey-Fuller test for unit root Number of obs = **129**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-1.960**	**-4.030**	**-3.446**	**-3.146**

MacKinnon approximate p-value for Z(t) = **0.6231**

4 . dfuller lsmokedfreshnpp, trend lags(1)

Augmented Dickey-Fuller test for unit root Number of obs = **130**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-6.414**	**-4.030**	**-3.446**	**-3.146**

MacKinnon approximate p-value for Z(t) = **0.0000**

5 . dfuller lpreparedfrozen, trend lags(2)

Augmented Dickey-Fuller test for unit root Number of obs = **129**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-5.137**	**-4.030**	**-3.446**	**-3.146**

MacKinnon approximate p-value for Z(t) = **0.0001**

6 . dfuller lpreparedfreshpp, trend lags(2)

Augmented Dickey-Fuller test for unit root Number of obs = **129**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-4.584**	**-4.030**	**-3.446**	**-3.146**

MacKinnon approximate p-value for Z(t) = **0.0011**

7 . dfuller lpreparedfreshnpp, trend lags(3)

Augmented Dickey-Fuller test for unit root Number of obs = **128**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-4.359**	**-4.031**	**-3.446**	**-3.146**

MacKinnon approximate p-value for Z(t) = **0.0025**

8 . dfuller lnaturalfrozen, trend lags(3)

Augmented Dickey-Fuller test for unit root Number of obs = **128**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-1.957**	**-4.031**	**-3.446**	**-3.146**

MacKinnon approximate p-value for Z(t) = **0.6246**

9 . dfuller lnaturalfreshpp, trend lags(4)

Augmented Dickey-Fuller test for unit root Number of obs = **127**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-3.638**	**-4.031**	**-3.446**	**-3.146**

MacKinnon approximate p-value for Z(t) = **0.0268**

10 . dfuller lnaturalfreshnpp, trend lags(4)

Augmented Dickey-Fuller test for unit root Number of obs = **127**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-2.722**	**-4.031**	**-3.446**	**-3.146**

MacKinnon approximate p-value for Z(t) = **0.2272**

11 .

Statistics/Data Analysis

User: 1

1 . dfuller d.lGermanyExport, lags(1)

Augmented Dickey-Fuller test for unit root Number of obs = **129**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-6.972**	**-3.500**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.0000**

2 . dfuller d.lsmokedfrozen, lags(4)

Augmented Dickey-Fuller test for unit root Number of obs = **64**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-4.224**	**-3.560**	**-2.919**	**-2.594**

MacKinnon approximate p-value for Z(t) = **0.0006**

3 . dfuller d.lsmokedfreshpp, lags(1)

Augmented Dickey-Fuller test for unit root Number of obs = **129**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-7.992**	**-3.500**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.0000**

4 . dfuller d.lsmokedfreshnpp, lags(4)

Augmented Dickey-Fuller test for unit root Number of obs = **126**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-6.878**	**-3.501**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.0000**

5 . dfuller d.lpreparedfrozen, lags(4)

Augmented Dickey-Fuller test for unit root Number of obs = **126**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-6.378**	**-3.501**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.0000**

6 . dfuller d.lpreparedfreshpp, lags(2)

Augmented Dickey-Fuller test for unit root Number of obs = **128**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-7.612**	**-3.501**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.0000**

7 . dfuller d.lpreparedfreshnpp, lags(2)

Augmented Dickey-Fuller test for unit root Number of obs = **128**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-9.795**	**-3.501**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.0000**

8 . dfuller d.lnaturalfrozen, lags(2)

Augmented Dickey-Fuller test for unit root Number of obs = **128**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-7.158**	**-3.501**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.0000**

9 . dfuller d.lnaturalfreshpp, lags(4)

Augmented Dickey-Fuller test for unit root Number of obs = **126**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-5.882**	**-3.501**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.0000**

10 . dfuller d.lnaturalfreshnpp, lags(4)

Augmented Dickey-Fuller test for unit root Number of obs = **126**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-6.401**	**-3.501**	**-2.888**	**-2.578**

MacKinnon approximate p-value for Z(t) = **0.0000**

11 .

```
                                                   ___  ____  ____  ____  ____(R)
                                                  /__    /   ____/   /   ____/
                                                 ___/   /   /___/   /   /___/
                                                   Statistics/Data Analysis

                                                     User: 1

1 . dfuller d.lGermanyExport, trend lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =       129

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -6.938            -4.030            -3.446            -3.146
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

2 . dfuller d.lsmokedfrozen, trend lags(4)

Augmented Dickey-Fuller test for unit root         Number of obs   =        64

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.067            -4.119            -3.486            -3.172
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0070

3 . dfuller d.lsmokedfreshpp, trend lags(1)

Augmented Dickey-Fuller test for unit root         Number of obs   =       129

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -7.963            -4.030            -3.446            -3.146
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

4 . dfuller d.lsmokedfreshnpp, trend lags(4)

Augmented Dickey-Fuller test for unit root         Number of obs   =       126

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -6.847            -4.031            -3.447            -3.147
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

5 . dfuller d.lpreparedfrozen, trend lags(4)

Augmented Dickey-Fuller test for unit root         Number of obs   =       126

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -6.355            -4.031            -3.447            -3.147
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

6 . dfuller d.lpreparedfreshpp, trend lags(2)

Augmented Dickey-Fuller test for unit root         Number of obs   =       128

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -7.583            -4.031            -3.446            -3.146
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

7 . dfuller d.lpreparedfreshnpp, trend lags(2)

Augmented Dickey-Fuller test for unit root Number of obs = **128**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-9.760**	**-4.031**	**-3.446**	**-3.146**

MacKinnon approximate p-value for Z(t) = **0.0000**

8 . dfuller d.lnaturalfrozen, trend lags(2)

Augmented Dickey-Fuller test for unit root Number of obs = **128**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-7.133**	**-4.031**	**-3.446**	**-3.146**

MacKinnon approximate p-value for Z(t) = **0.0000**

9 . dfuller d.lnaturalfreshpp, trend lags(3)

Augmented Dickey-Fuller test for unit root Number of obs = **127**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-8.173**	**-4.031**	**-3.446**	**-3.146**

MacKinnon approximate p-value for Z(t) = **0.0000**

10 . dfuller d.lnaturalfreshnpp, trend lags(4)

Augmented Dickey-Fuller test for unit root Number of obs = **126**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-6.366**	**-4.031**	**-3.447**	**-3.147**

MacKinnon approximate p-value for Z(t) = **0.0000**

11 .

Statistics/Data Analysis

User: 1

```
1 . reg lsmokedfreshpp lGermanyExport

      Source |       SS           df       MS      Number of obs   =       132
-------------+----------------------------------   F(1, 130)       =    330.67
       Model |   2.2889296         1   2.2889296   Prob > F        =    0.0000
    Residual |  .899863392       130  .006922026   R-squared       =    0.7178
-------------+----------------------------------   Adj R-squared   =    0.7156
       Total |  3.18879299       131  .024341931   Root MSE        =     .0832

------------------------------------------------------------------------------
lsmokedfreshpp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
lGermanyExport |   .4345249   .0238954    18.18   0.000     .3872506    .4817992
         _cons |   2.315611   .0324845    71.28   0.000     2.251344    2.379877
------------------------------------------------------------------------------

2 . reg lsmokedfreshnpp lGermanyExport

      Source |       SS           df       MS      Number of obs   =       132
-------------+----------------------------------   F(1, 130)       =      0.50
       Model |  .003928628         1  .003928628   Prob > F        =    0.4824
    Residual |  1.02931075       130  .007917775   R-squared       =    0.0038
-------------+----------------------------------   Adj R-squared   =   -0.0039
       Total |  1.03323937       131  .007887323   Root MSE        =    .08898

------------------------------------------------------------------------------
lsmokedfre~npp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
lGermanyExport |   .0180019   .0255564     0.70   0.482    -.0325584    .0685622
         _cons |   2.788622   .0347425    80.27   0.000     2.719888    2.857356
------------------------------------------------------------------------------

3 . reg lpreparedfrozen lGermanyExport

      Source |       SS           df       MS      Number of obs   =       132
-------------+----------------------------------   F(1, 130)       =     36.78
       Model |  1.08720759         1  1.08720759   Prob > F        =    0.0000
    Residual |  3.84254132       130   .02955801   R-squared       =    0.2205
-------------+----------------------------------   Adj R-squared   =    0.2145
       Total |  4.92974891       131  .037631671   Root MSE        =    .17192

------------------------------------------------------------------------------
lpreparedfro~n |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
lGermanyExport |   .2994709   .0493783     6.06   0.000     .2017819      .39716
         _cons |    2.00885   .0671269    29.93   0.000     1.876047    2.141652
------------------------------------------------------------------------------

4 . reg lpreparedfreshpp lGermanyExport

      Source |       SS           df       MS      Number of obs   =       132
-------------+----------------------------------   F(1, 130)       =     88.76
       Model |  2.86047545         1  2.86047545   Prob > F        =    0.0000
    Residual |  4.18945284       130   .03222656   R-squared       =    0.4057
-------------+----------------------------------   Adj R-squared   =    0.4012
       Total |  7.04992829       131  .053816247   Root MSE        =    .17952

------------------------------------------------------------------------------
lpreparedf~hpp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
---------------+----------------------------------------------------------------
lGermanyExport |   .4857553   .0515591     9.42   0.000     .3837518    .5877588
         _cons |   2.101781   .0700916    29.99   0.000     1.963113    2.240449
------------------------------------------------------------------------------
```

```
5 . reg lpreparedfreshnpp lGermanyExport

      Source |       SS           df       MS      Number of obs   =       132
-------------+----------------------------------   F(1, 130)       =      0.02
       Model |  .000194676         1  .000194676   Prob > F        =    0.8969
    Residual |  1.50081487       130   .01154473   R-squared       =    0.0001
-------------+----------------------------------   Adj R-squared   =   -0.0076
       Total |  1.50100955       131  .011458088   Root MSE        =    .10745

------------------------------------------------------------------------------
lpreparedf~npp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
lGermanyExport |  -.0040073   .0308596    -0.13   0.897    -.0650594    .0570447
         _cons |   2.783314   .0419518    66.35   0.000     2.700317     2.86631
------------------------------------------------------------------------------

6 . reg lnaturalfrozen lGermanyExport

      Source |       SS           df       MS      Number of obs   =       132
-------------+----------------------------------   F(1, 130)       =     89.43
       Model |  .941917459         1  .941917459   Prob > F        =    0.0000
    Residual |  1.36920677       130   .01053236   R-squared       =    0.4076
-------------+----------------------------------   Adj R-squared   =    0.4030
       Total |  2.31112423       131   .01764217   Root MSE        =    .10263

------------------------------------------------------------------------------
lnaturalfrozen |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
lGermanyExport |   .2787436   .0294755     9.46   0.000     .2204298    .3370573
         _cons |   2.142346   .0400702    53.46   0.000     2.063072     2.22162
------------------------------------------------------------------------------

7 . reg lnaturalfreshpp lGermanyExport

      Source |       SS           df       MS      Number of obs   =       132
-------------+----------------------------------   F(1, 130)       =    109.70
       Model |  2.33369923         1  2.33369923   Prob > F        =    0.0000
    Residual |  2.76546553       130  .021272812   R-squared       =    0.4577
-------------+----------------------------------   Adj R-squared   =    0.4535
       Total |  5.09916475       131  .038924922   Root MSE        =    .14585

------------------------------------------------------------------------------
lnaturalfr~hpp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
lGermanyExport |   .4387538   .0418901    10.47   0.000     .3558793    .5216282
         _cons |   1.961565   .0569471    34.45   0.000     1.848902    2.074228
------------------------------------------------------------------------------

8 . reg lnaturalfreshnpp lGermanyExport

      Source |       SS           df       MS      Number of obs   =       132
-------------+----------------------------------   F(1, 130)       =    663.49
       Model |  2.98702926         1  2.98702926   Prob > F        =    0.0000
    Residual |  .585262291       130  .004502018   R-squared       =    0.8362
-------------+----------------------------------   Adj R-squared   =    0.8349
       Total |  3.57229155       131  .027269401   Root MSE        =     .0671

------------------------------------------------------------------------------
lnaturalfr~npp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
lGermanyExport |   .4963845   .0192709    25.76   0.000     .4582593    .5345096
         _cons |   2.253861   .0261977    86.03   0.000     2.202032     2.30569
------------------------------------------------------------------------------

9 .
```

```
1 . varsoc lsmokedfreshpp lGermanyExport
```

Selection-order criteria
Sample: **2009m5 - 2019m12** Number of obs = **128**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**110.211**				**.000632**	**-1.69079**	**-1.67269**	**-1.64623**
1	**447.753**	**675.09**	**4**	**0.000**	**3.4e-06**	**-6.9024**	**-6.84808**	**-6.76871***
2	**456.398**	**17.289***	**4**	**0.002**	**3.2e-06***	**-6.97497***	**-6.88444***	**-6.75216**
3	**457.537**	**2.2778**	**4**	**0.685**	**3.4e-06**	**-6.93027**	**-6.80352**	**-6.61833**
4	**458.78**	**2.4864**	**4**	**0.647**	**3.5e-06**	**-6.88719**	**-6.72424**	**-6.48613**

Endogenous: lsmokedfreshpp lGermanyExport
Exogenous: _cons

```
2 . varsoc lsmokedfreshnpp lGermanyExport
```

Selection-order criteria
Sample: **2009m5 - 2019m12** Number of obs = **128**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**100.854**				**.000732**	**-1.54459**	**-1.52648**	**-1.50003**
1	**281.952**	**362.2***	**4**	**0.000**	**.000046***	**-4.31176***	**-4.25744***	**-4.17807***
2	**284.25**	**4.5952**	**4**	**0.331**	**.000047**	**-4.28516**	**-4.19463**	**-4.06234**
3	**285.594**	**2.6873**	**4**	**0.611**	**.000049**	**-4.24365**	**-4.11691**	**-3.93171**
4	**288.042**	**4.8967**	**4**	**0.298**	**.00005**	**-4.21941**	**-4.05645**	**-3.81834**

Endogenous: lsmokedfreshnpp lGermanyExport
Exogenous: _cons

```
3 . varsoc lpreparedfrozen lGermanyExport
```

Selection-order criteria
Sample: **2009m5 - 2019m12** Number of obs = **128**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**18.6556**				**.002643**	**-.260244**	**-.242138**	**-.215681**
1	**230.218**	**423.12**	**4**	**0.000**	**.000103**	**-3.5034**	**-3.44908***	**-3.36971***
2	**234.851**	**9.2657**	**4**	**0.055**	**.000102**	**-3.51329**	**-3.42276**	**-3.29047**
3	**236.171**	**2.6419**	**4**	**0.619**	**.000107**	**-3.47143**	**-3.34469**	**-3.15949**
4	**242.987**	**13.63***	**4**	**0.009**	**.000102***	**-3.51542***	**-3.35246**	**-3.11435**

Endogenous: lpreparedfrozen lGermanyExport
Exogenous: _cons

```
4 . varsoc lpreparedfreshpp lGermanyExport
```

Selection-order criteria
Sample: **2009m5 - 2019m12** Number of obs = **128**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**9.70605**				**.003039**	**-.120407**	**-.102301**	**-.075844**
1	**230.133**	**440.85**	**4**	**0.000**	**.000103**	**-3.50208**	**-3.44776***	**-3.36839***
2	**235.747**	**11.228***	**4**	**0.024**	**.000101**	**-3.5273**	**-3.43677**	**-3.30448**
3	**239.945**	**8.3951**	**4**	**0.078**	**.0001***	**-3.53038***	**-3.40364**	**-3.21844**
4	**242.63**	**5.3717**	**4**	**0.251**	**.000103**	**-3.50985**	**-3.3469**	**-3.10878**

Endogenous: lpreparedfreshpp lGermanyExport
Exogenous: _cons

```
5 . varsoc lpreparedfreshnpp lGermanyExport

   Selection-order criteria
   Sample:  2009m5 - 2019m12                    Number of obs      =       128
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	76.8549				.001064	-1.16961	-1.1515	-1.12504
1	264.635	375.56*	4	0.000	.00006*	-4.04117*	-3.98685*	-3.90748*
2	266.985	4.7	4	0.319	.000062	-4.01538	-3.92485	-3.79257
3	270.868	7.767	4	0.100	.000062	-4.01356	-3.88682	-3.70162
4	273.046	4.3549	4	0.360	.000064	-3.98509	-3.82213	-3.58402

```
   Endogenous:  lpreparedfreshnpp lGermanyExport
    Exogenous:  _cons

6 . varsoc lnaturalfrozen lGermanyExport

   Selection-order criteria
   Sample:  2009m5 - 2019m12                    Number of obs      =       128
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	82.7899				.00097	-1.26234	-1.24424	-1.21778
1	387.573	609.57	4	0.000	8.8e-06	-5.96208	-5.90777	-5.82839*
2	393.968	12.79	4	0.012	8.5e-06	-5.99951	-5.90898	-5.77669
3	401.515	15.094*	4	0.005	8.0e-06*	-6.05493*	-5.92819*	-5.74299
4	405.427	7.8229	4	0.098	8.1e-06	-6.05355	-5.89059	-5.65248

```
   Endogenous:  lnaturalfrozen lGermanyExport
    Exogenous:  _cons

7 . varsoc lnaturalfreshpp lGermanyExport

   Selection-order criteria
   Sample:  2009m5 - 2019m12                    Number of obs      =       128
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	38.9				.001926	-.576562	-.558456	-.531999
1	239.342	400.88	4	0.000	.000089	-3.64597	-3.59165	-3.51228
2	248.184	17.684	4	0.001	.000083	-3.72162	-3.63109	-3.49881
3	259.102	21.836*	4	0.000	.000074*	-3.82971*	-3.70297*	-3.51777*
4	260.325	2.446	4	0.654	.000078	-3.78632	-3.62336	-3.38525

```
   Endogenous:  lnaturalfreshpp lGermanyExport
    Exogenous:  _cons

8 . varsoc lnaturalfreshnpp lGermanyExport

   Selection-order criteria
   Sample:  2009m5 - 2019m12                    Number of obs      =       128
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	138.346				.000407	-2.1304	-2.1123	-2.08584
1	342.888	409.08*	4	0.000	.000018*	-5.26388*	-5.20956*	-5.13019*
2	346.807	7.8366	4	0.098	.000018	-5.2626	-5.17207	-5.03979
3	350.154	6.6945	4	0.153	.000018	-5.2524	-5.12566	-4.94046
4	353.585	6.8629	4	0.143	.000018	-5.24352	-5.08056	-4.84245

```
   Endogenous:  lnaturalfreshnpp lGermanyExport
    Exogenous:  _cons

9 .
```

1 . vecrank lsmokedfreshpp lGermanyExport, trend(rtrend) lags(2) ic max

Johansen tests for cointegration

Trend: rtrend   Number of obs = **130**

Sample: **2009m3 - 2019m12**   Lags = **2**

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	6	450.53495	.	32.1472	25.32
1	10	463.82362	0.18490	5.5698*_	12.25
2	12	466.60854	0.04194		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	6	450.53495	.	26.5773	18.96
1	10	463.82362	0.18490	5.5698	12.52
2	12	466.60854	0.04194		

maximum rank	parms	LL	eigenvalue	SBIC	HQIC	AIC
0	6	450.53495		-6.706652	-6.785222	-6.838999
1	10	463.82362	0.18490	-6.761322*	-6.892273*	-6.981902
2	12	466.60854	0.04194	-6.729282	-6.886423	-6.993978

2 . vecrank lsmokedfreshnpp lGermanyExport, trend(rtrend) lags(1) ic max

Johansen tests for cointegration

Trend: rtrend   Number of obs = **131**

Sample: **2009m2 - 2019m12**   Lags = **1**

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	2	257.89306	.	70.3647	25.32
1	6	289.63072	0.38402	6.8894*_	12.25
2	8	293.07541	0.05123		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	2	257.89306	.	63.4753	18.96
1	6	289.63072	0.38402	6.8894	12.52
2	8	293.07541	0.05123		

maximum rank	parms	LL	eigenvalue	SBIC	HQIC	AIC
0	2	257.89306		-3.862868	-3.888927	-3.906764
1	6	289.63072	0.38402	-4.198552*	-4.276729*	-4.33024
2	8	293.07541	0.05123	-4.176712	-4.280949	-4.352296

3 . vecrank lpreparedfrozen lGermanyExport, trend(rtrend) lags(4) ic max

Johansen tests for cointegration

Trend: rtrend   Number of obs = **128**

Sample: **2009m5 - 2019m12**   Lags = **4**

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	14	233.52337	.	36.9716	25.32
1	18	247.62992	0.19781	8.7585*_	12.25
2	20	252.00916	0.06614		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	14	233.52337	.	28.2131	18.96
1	18	247.62992	0.19781	8.7585	12.52
2	20	252.00916	0.06614		

maximum rank	parms	LL	eigenvalue	SBIC	HQIC	AIC
0	14	233.52337		-3.118112	-3.303309	-3.430053
1	18	247.62992	0.19781	-3.186901*	-3.425012*	-3.587967
2	20	252.00916	0.06614	-3.179513	-3.444081	-3.625143

```
4 . vecrank lpreparedfreshpp lGermanyExport, trend(rtrend) lags(3) ic max
```

Johansen tests for cointegration

Trend: rtrend Number of obs = **129**

Sample: **2009m4 - 2019m12** Lags = **3**

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	10	233.66813	.	27.4078	25.32
1	14	242.42442	0.12694	9.8952*_	12.25
2	16	247.37201	0.07384		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	10	233.66813	.	17.5126	18.96
1	14	242.42442	0.12694	9.8952	12.52
2	16	247.37201	0.07384		

maximum rank	parms	LL	eigenvalue	SBIC	HQIC	AIC
0	10	233.66813		-3.246032*	-3.377645	-3.467723
1	14	242.42442	0.12694	-3.231097	-3.415355*	-3.541464
2	16	247.37201	0.07384	-3.232457	-3.443039	-3.587163

```
5 . vecrank lpreparedfreshnpp lGermanyExport, trend(rtrend) lags(1) ic max
```

Johansen tests for cointegration

Trend: rtrend Number of obs = **131**

Sample: **2009m2 - 2019m12** Lags = **1**

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	2	237.61201	.	75.8035	25.32
1	6	271.71798	0.40590	7.5916*_	12.25
2	8	275.51378	0.05630		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	2	237.61201	.	68.2119	18.96
1	6	271.71798	0.40590	7.5916	12.52
2	8	275.51378	0.05630		

maximum rank	parms	LL	eigenvalue	SBIC	HQIC	AIC
0	2	237.61201		-3.553234	-3.579293	-3.59713
1	6	271.71798	0.40590	-3.925075*	-4.003252*	-4.056763
2	8	275.51378	0.05630	-3.908595	-4.012832	-4.08418

```
6 . vecrank lnaturalfrozen lGermanyExport, trend(rtrend) lags(3) ic max
```

Johansen tests for cointegration

Trend: rtrend Number of obs = **129**
Sample: **2009m4 - 2019m12** Lags = **3**

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	10	400.73131	.	18.5089*	25.32
1	14	408.0268	0.10695	3.9179	12.25
2	16	409.98575	0.02991		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	10	400.73131	.	14.5910	18.96
1	14	408.0268	0.10695	3.9179	12.52
2	16	409.98575	0.02991		

maximum rank	parms	LL	eigenvalue	SBIC	HQIC	AIC
0	10	400.73131		-5.836159*	-5.967772	-6.05785
1	14	408.0268	0.10695	-5.798575	-5.982834*	-6.108943
2	16	409.98575	0.02991	-5.753601	-5.964182	-6.108306

```
7 . vecrank lnaturalfreshpp lGermanyExport, trend(rtrend) lags(3) ic max
```

Johansen tests for cointegration

Trend: rtrend Number of obs = **129**
Sample: **2009m4 - 2019m12** Lags = **3**

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	10	254.06616	.	27.9203	25.32
1	14	262.51795	0.12281	11.0167*	12.25
2	16	268.02632	0.08186		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	10	254.06616	.	16.9036	18.96
1	14	262.51795	0.12281	11.0167	12.52
2	16	268.02632	0.08186		

maximum rank	parms	LL	eigenvalue	SBIC	HQIC	AIC
0	10	254.06616		-3.562281*	-3.693894	-3.783972
1	14	262.51795	0.12281	-3.542624	-3.726883*	-3.852992
2	16	268.02632	0.08186	-3.552679	-3.763261	-3.907385

```
8 . vecrank lnaturalfreshnpp lGermanyExport, trend(rtrend) lags(1) ic max
```

Johansen tests for cointegration

Trend: rtrend Number of obs = **131**
Sample: **2009m2 - 2019m12** Lags = **1**

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	2	323.9512	.	80.5551	25.32
1	6	360.08513	0.42401	8.2872*	12.25
2	8	364.22874	0.06130		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	2	323.9512	.	72.2679	18.96
1	6	360.08513	0.42401	8.2872	12.52
2	8	364.22874	0.06130		

maximum rank	parms	LL	eigenvalue	SBIC	HQIC	AIC
0	**2**	**323.9512**		**-4.871389**	**-4.897449**	**-4.915285**
1	**6**	**360.08513**	**0.42401**	**-5.274191***	**-5.352369***	**-5.40588**
2	**8**	**364.22874**	**0.06130**	**-5.263022**	**-5.367259**	**-5.438607**

9 .

```
      ___  ____  ____  ____  ____(R)
     /__    /   ____/   /   ____/
    ___/   /   /___/   /   /___/
      Statistics/Data Analysis

        User: 1

1 . constraint 1 _b[lsmokedfreshpp] = 1

2 .
3 . constraint 2 _b[lGermanyExport] = -1

4 .
5 . vec lsmokedfreshpp lGermanyExport, trend(rtrend) rank(1) lags(2) bconstraint(1/2)

  Iteration 1:     log likelihood = 463.31378
  Iteration 2:     log likelihood = 463.31584
  Iteration 3:     log likelihood = 463.31584

  Vector error-correction model

  Sample:  2009m3 - 2019m12                       Number of obs     =        130
                                                  AIC               =  -6.989474
  Log likelihood =  463.3158                      HQIC              =  -6.908808
  Det(Sigma_ml)  =  2.75e-06                      SBIC              =  -6.790953

  Equation           Parms      RMSE     R-sq      chi2     P>chi2
  ----------------------------------------------------------------
  D_lsmokedfreshpp     4     .023405   0.1673   25.31261   0.0000
  D_lGermanyExport     4     .073732   0.0834   11.46589   0.0218
  ----------------------------------------------------------------

  ------------------------------------------------------------------------------------
                    |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
  ------------------+-----------------------------------------------------------------
  D_lsmokedfreshpp  |
               _ce1 |
                L1. |  -.0585844   .0140869    -4.16   0.000    -.0861943   -.0309746
                    |
     lsmokedfreshpp |
                LD. |  -.2212197   .0827249    -2.67   0.007    -.3833575    -.059082
                    |
     lGermanyExport |
                LD. |  -.0522378   .0289027    -1.81   0.071     -.108886    .0044104
                    |
              _cons |   .0059509   .0021158     2.81   0.005      .001804    .0100978
  ------------------+-----------------------------------------------------------------
  D_lGermanyExport  |
               _ce1 |
                L1. |   .1157818   .0443768     2.61   0.009     .0288048    .2027588
                    |
     lsmokedfreshpp |
                LD. |  -.0832702   .2606011    -0.32   0.749     -.594039    .4274986
                    |
     lGermanyExport |
                LD. |    .229102   .0910496     2.52   0.012      .050648    .4075559
                    |
              _cons |   .0030111   .0066653     0.45   0.651    -.0100526    .0160748
  ------------------------------------------------------------------------------------

  Cointegrating equations

  Equation           Parms    chi2     P>chi2
  -------------------------------------------
  _ce1                 0         .         .
  -------------------------------------------

  Identification:  beta is overidentified
```

```
 ( 1)  [_ce1]lsmokedfreshpp = 1
 ( 2)  [_ce1]lGermanyExport = -1
------------------------------------------------------------------------------------
           beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------+-------------------------------------------------------------------
_ce1            |
lsmokedfreshpp  |          1          .       .       .            .           .
lGermanyExport  |         -1          .       .       .            .           .
         _trend |   .0030829   .0007421    4.15   0.000     .0016284    .0045375
          _cons |  -1.742696          .       .       .            .           .
------------------------------------------------------------------------------------
LR test of identifying restrictions: chi2(1) = 1.016       Prob > chi2 = 0.314

 6 . test ([D_lsmokedfreshpp]: L._ce1)

 ( 1)  [D_lsmokedfreshpp]L._ce1 = 0

           chi2(  1) =   17.30
         Prob > chi2 =    0.0000

 7 . test ([D_lGermanyExport]: L._ce1)

 ( 1)  [D_lGermanyExport]L._ce1 = 0

           chi2(  1) =    6.81
         Prob > chi2 =    0.0091

 8 . constraint 1 _b[lsmokedfreshnpp] = 1

 9 .
10 . constraint 2 _b[lGermanyExport] = -1

11 .
12 . vec lsmokedfreshnpp lGermanyExport, trend(rtrend) rank(1) lags(1) bconstraint(1/2)

Iteration 1:     log likelihood = 266.42841
Iteration 2:     log likelihood = 266.42889
Iteration 3:     log likelihood = 266.42889
Iteration 4:     log likelihood = 266.42889

Vector error-correction model

Sample:  2009m2 - 2019m12                        Number of obs     =        131
                                                 AIC               =  -3.991281
Log likelihood =  266.4289                       HQIC              =  -3.946688
Det(Sigma_ml)  =  .0000587                       SBIC              =   -3.88154

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
D_lsmokedfresh~p      2     .104494   0.0897   12.71039   0.0017
D_lGermanyExport      2      .07477   0.0357   4.773009   0.0920
----------------------------------------------------------------

------------------------------------------------------------------------------------
                |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------+-------------------------------------------------------------------
D_lsmokedfreshnpp |
           _ce1 |
            L1. |  -.1746537   .0490095   -3.56   0.000    -.2707106   -.0785968
                |
          _cons |   .0020538   .0091683    0.22   0.823    -.0159157    .0200232
----------------+-------------------------------------------------------------------
D_lGermanyExport |
           _ce1 |
            L1. |     .06844   .0350686    1.95   0.051    -.0002932    .1371731
                |
          _cons |    .005241   .0065603    0.80   0.424     -.007617     .018099
------------------------------------------------------------------------------------

Cointegrating equations
```

Equation	Parms	chi2	P>chi2
_ce1	**0**	.	.

```
Identification:  beta is overidentified

 ( 1)  [_ce1]lsmokedfreshnpp = 1
 ( 2)  [_ce1]lGermanyExport = -1
```

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lsmokedfreshnpp	**1**	.	.	.	.	.
lGermanyExport	**-1**	.	.	.	.	.
_trend	**.0064998**	**.0011625**	**5.59**	**0.000**	**.0042213**	**.0087783**
_cons	**-1.896293**	.	.	.	.	.

LR test of identifying restrictions: chi2(**1**) = **46.4** Prob > chi2 = **0.000**

```
13 . test ([D_lsmokedfreshnpp]: L._ce1)

 ( 1)  [D_lsmokedfreshnpp]L._ce1 = 0

           chi2(  1) =   12.70
         Prob > chi2 =    0.0004

14 . test ([D_lGermanyExport]: L._ce1)

 ( 1)  [D_lGermanyExport]L._ce1 = 0

           chi2(  1) =    3.81
         Prob > chi2 =    0.0510

15 . constraint 1 _b[lpreparedfrozen] = 1

16 .
17 . constraint 2 _b[lGermanyExport] = -1

18 .
19 . vec lpreparedfrozen lGermanyExport, trend(rtrend) rank(1) lags(4) bconstraint(1/2)

Iteration 1:     log likelihood = 239.65982
Iteration 2:     log likelihood = 239.68304
Iteration 3:     log likelihood = 239.68304
Iteration 4:     log likelihood = 239.68304

Vector error-correction model

Sample:  2009m5 - 2019m12                    Number of obs     =         128
                                             AIC               =   -3.479422
Log likelihood =   239.683                   HQIC              =    -3.32552
Det(Sigma_ml)  =   .000081                   SBIC              =   -3.100637
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lpreparedfro~n	**8**	**.133324**	**0.1896**	**28.07466**	**0.0005**
D_lGermanyExport	**8**	**.072136**	**0.1611**	**23.04666**	**0.0033**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lpreparedfrozen						
_ce1						
L1.	**-.1558471**	**.0569031**	**-2.74**	**0.006**	**-.2673752**	**-.044319**
lpreparedfrozen						
LD.	**-.2638487**	**.0920219**	**-2.87**	**0.004**	**-.4442083**	**-.083489**
L2D.	**-.0839892**	**.0937402**	**-0.90**	**0.370**	**-.2677167**	**.0997383**
L3D.	**-.041955**	**.0900397**	**-0.47**	**0.641**	**-.2184296**	**.1345195**
lGermanyExport						
LD.	**-.2377531**	**.1632483**	**-1.46**	**0.145**	**-.5577139**	**.0822076**

```
             L2D.  |  -.0335187   .1678626    -0.20   0.842    -.3625233     .295486
             L3D.  |   .1737997   .1672302     1.04   0.299    -.1539655    .5015649
                   |
            _cons  |    .003057   .0118884     0.26   0.797    -.0202439    .0263579
-------------------+----------------------------------------------------------------
D_lGermanyExport   |
             _ce1  |
              L1.  |   .0611855    .030788     1.99   0.047     .0008421    .1215289
                   |
  lpreparedfrozen  |
              LD.  |  -.0621634   .0497894    -1.25   0.212    -.1597487     .035422
             L2D.  |  -.1487177   .0507191    -2.93   0.003    -.2481252   -.0493101
             L3D.  |    -.1678    .0487169    -3.44   0.001    -.2632833   -.0723167
                   |
   lGermanyExport  |
              LD.  |   .1545361   .0883271     1.75   0.080    -.0185818     .327654
             L2D.  |    .103159   .0908237     1.14   0.256    -.0748523    .2811702
             L3D.  |   -.067993   .0904816    -0.75   0.452    -.2453336    .1093476
                   |
            _cons  |   .0077866   .0064324     1.21   0.226    -.0048206    .0203937
------------------------------------------------------------------------------------

Cointegrating equations

Equation           Parms    chi2     P>chi2
-------------------------------------------
_ce1                   0       .         .
-------------------------------------------

Identification:  beta is overidentified

 ( 1)  [_ce1]lpreparedfrozen = 1
 ( 2)  [_ce1]lGermanyExport = -1
--------------------------------------------------------------------------------
            beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+--------------------------------------------------------------
_ce1             |
 lpreparedfrozen |          1          .        .       .            .           .
  lGermanyExport |         -1          .        .       .            .           .
          _trend |   .0038329   .0016123     2.38   0.017     .0006728    .0069931
           _cons |  -1.340685          .        .       .            .           .
--------------------------------------------------------------------------------
LR test of identifying restrictions: chi2(1) = 15.89      Prob > chi2 = 0.000

20 . test ([D_lpreparedfrozen]: L._ce1)

 ( 1)  [D_lpreparedfrozen]L._ce1 = 0

           chi2(  1) =    7.50
         Prob > chi2 =    0.0062

21 . test ([D_lGermanyExport]: L._ce1)

 ( 1)  [D_lGermanyExport]L._ce1 = 0

           chi2(  1) =    3.95
         Prob > chi2 =    0.0469

22 . constraint 1 _b[lpreparedfreshpp] = 1

23 .
24 . constraint 2 _b[lGermanyExport] = -1
```

```
25 .
26 . vec lpreparedfreshpp lGermanyExport, trend(rtrend) rank(1) lags(3) bconstraint(1/2)

   Iteration 1:     log likelihood = 240.81104
   Iteration 2:     log likelihood = 240.81896
   Iteration 3:     log likelihood = 240.81896
   Iteration 4:     log likelihood = 240.81896

   Vector error-correction model

   Sample:  2009m4 - 2019m12                          Number of obs     =         129
                                                      AIC               =   -3.532077
   Log likelihood =   240.819                         HQIC              =   -3.414976
   Det(Sigma_ml)  =   .000082                         SBIC              =   -3.243879

   Equation           Parms      RMSE     R-sq      chi2     P>chi2
   ----------------------------------------------------------------
   D_lpreparedfre~p     6      .13467   0.1711   25.38262   0.0003
   D_lGermanyExport     6     .071237   0.1628   23.91195   0.0005
   ----------------------------------------------------------------

   ------------------------------------------------------------------------------------
                      |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
   -------------------+----------------------------------------------------------------
   D_lpreparedfreshpp |
                 _ce1 |
                  L1. |    -.11636   .0616887    -1.89   0.059    -.2372677    .0045477
                      |
     lpreparedfreshpp |
                  LD. |  -.2491634   .0981165    -2.54   0.011    -.4414682   -.0568586
                 L2D. |  -.0680174   .0916248    -0.74   0.458    -.2475988     .111564
                      |
       lGermanyExport |
                  LD. |  -.3578343    .161738    -2.21   0.027     -.674835   -.0408337
                 L2D. |   -.346334   .1670435    -2.07   0.038    -.6737333   -.0189347
                      |
                _cons |   .0061769   .0120574     0.51   0.608    -.0174552    .0298089
   -------------------+----------------------------------------------------------------
   D_lGermanyExport   |
                 _ce1 |
                  L1. |   .0976114   .0326316     2.99   0.003     .0336545    .1615682
                      |
     lpreparedfreshpp |
                  LD. |   .0459586   .0519009     0.89   0.376    -.0557653    .1476825
                 L2D. |   .0748142    .048467     1.54   0.123    -.0201793    .1698078
                      |
       lGermanyExport |
                  LD. |    .132711   .0855549     1.55   0.121    -.0349735    .3003955
                 L2D. |   .1134745   .0883614     1.28   0.199    -.0597106    .2866596
                      |
                _cons |   .0073633    .006378     1.15   0.248    -.0051374     .019864
   ------------------------------------------------------------------------------------

   Cointegrating equations

   Equation           Parms    chi2     P>chi2
   -------------------------------------------
   _ce1                 0         .         .
   -------------------------------------------

   Identification:  beta is overidentified

    ( 1)  [_ce1]lpreparedfreshpp = 1
    ( 2)  [_ce1]lGermanyExport = -1
   ----------------------------------------------------------------------------------
               beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
   -----------------+----------------------------------------------------------------
   _ce1             |
   lpreparedfreshpp |          1          .        .       .            .           .
     lGermanyExport |         -1          .        .       .            .           .
             _trend |   .0022928   .0013598     1.69   0.092    -.0003724     .004958
              _cons |  -1.591998          .        .       .            .           .
   ----------------------------------------------------------------------------------
   LR test of identifying restrictions: chi2(1) = 3.211        Prob > chi2 = 0.073
```

```
27 . test ([D_lpreparedfreshpp]: L._ce1)

    ( 1)  [D_lpreparedfreshpp]L._ce1 = 0

              chi2(  1) =    3.56
            Prob > chi2 =    0.0593

28 . test ([D_lGermanyExport]: L._ce1)

    ( 1)  [D_lGermanyExport]L._ce1 = 0

              chi2(  1) =    8.95
            Prob > chi2 =    0.0028

29 . constraint 1 _b[lpreparedfreshnpp] = 1

30 .
31 . constraint 2 _b[lGermanyExport] = -1

32 .
33 . vec lpreparedfreshnpp lGermanyExport, trend(rtrend) rank(1) lags(1) bconstraint(1/2)

   Iteration 1:     log likelihood = 250.52274
   Iteration 2:     log likelihood = 250.52487
   Iteration 3:     log likelihood = 250.52487
   Iteration 4:     log likelihood = 250.52487

   Vector error-correction model

   Sample:  2009m2 - 2019m12                      Number of obs     =        131
                                                  AIC               =  -3.748471
   Log likelihood =  250.5249                     HQIC              =  -3.703879
   Det(Sigma_ml)  =  .0000748                     SBIC              =  -3.638731
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lpreparedfre~p	2	.117016	0.1747	27.30569	0.0000
D_lGermanyExport	2	.07534	0.0209	2.756056	0.2521

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lpreparedfreshnpp						
_ce1						
L1.	-.2724775	.0521446	-5.23	0.000	-.374679	-.1702759
_cons	.001041	.0102248	0.10	0.919	-.0189993	.0210813
D_lGermanyExport						
_ce1						
L1.	.0451222	.033573	1.34	0.179	-.0206797	.1109241
_cons	.0062863	.0065832	0.95	0.340	-.0066165	.0191892

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	0	.	.

Identification: beta is overidentified

(1) **[_ce1]lpreparedfreshnpp = 1**
(2) **[_ce1]lGermanyExport = -1**

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lpreparedfreshnpp	1	.	.	.	.	.
lGermanyExport	-1	.	.	.	.	.
_trend	.0065984	.0009779	6.75	0.000	.0046818	.0085151
_cons	-1.881676	.	.	.	.	.

LR test of identifying restrictions: chi2(**1**) = **42.39** Prob > chi2 = **0.000**

34 . test ([D_lpreparedfreshnpp]: L._ce1)

(1) **[D_lpreparedfreshnpp]L._ce1 = 0**

chi2(1) = **27.31**
Prob > chi2 = **0.0000**

35 . test ([D_lGermanyExport]: L._ce1)

(1) **[D_lGermanyExport]L._ce1 = 0**

chi2(1) = **1.81**
Prob > chi2 = **0.1789**

36 . constraint 1 _b[lnaturalfrozen] = 1

37 .
38 . constraint 2 _b[lGermanyExport] = -1

39 .
40 . vec lnaturalfrozen lGermanyExport, trend(rtrend) rank(1) lags(3) bconstraint(1/2)

Iteration 1: log likelihood = **406.67134**
Iteration 2: log likelihood = **406.80586**
Iteration 3: log likelihood = **406.80589**
Iteration 4: log likelihood = **406.80589**
Iteration 5: log likelihood = **406.80589**

Vector error-correction model

Sample: **2009m4 - 2019m12** Number of obs = **129**
AIC = **-6.105518**
Log likelihood = **406.8059** HQIC = **-5.988417**
Det(Sigma_ml) = **6.25e-06** SBIC = **-5.817319**

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lnaturalfrozen	6	.036219	0.1999	30.7297	0.0000
D_lGermanyExport	6	.073118	0.1180	16.44934	0.0115

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lnaturalfrozen						
_ce1						
L1.	-.0574627	.0181772	-3.16	0.002	-.0930894	-.0218359
lnaturalfrozen						
LD.	-.3148685	.0853214	-3.69	0.000	-.4820955	-.1476415
L2D.	-.2166682	.0844337	-2.57	0.010	-.3821552	-.0511812
lGermanyExport						
LD.	.0370349	.0448107	0.83	0.409	-.0507925	.1248623
L2D.	.0022023	.046163	0.05	0.962	-.0882755	.0926802
_cons	.0062592	.0033049	1.89	0.058	-.0002183	.0127368
D_lGermanyExport						
_ce1						
L1.	.0695978	.0366954	1.90	0.058	-.002324	.1415195

```
                  |
  lnaturalfrozen  |
              LD. |  -.1377271   .1722432    -0.80   0.424    -.4753176    .1998634
             L2D. |  -.4530286   .1704511    -2.66   0.008    -.7871065   -.1189506
                  |
  lGermanyExport  |
              LD. |   .1857881   .0904619     2.05   0.040      .008486    .3630901
             L2D. |   .0687138   .0931919     0.74   0.461    -.1139389    .2513664
                  |
            _cons |   .0051679   .0066719     0.77   0.439    -.0079088    .0182445
-----------------------------------------------------------------------------------

Cointegrating equations

Equation           Parms    chi2     P>chi2
-------------------------------------------
_ce1                 0         .         .
-------------------------------------------

Identification:  beta is overidentified

 ( 1)  [_ce1]lnaturalfrozen = 1
 ( 2)  [_ce1]lGermanyExport = -1
---------------------------------------------------------------------------------
           beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------+----------------------------------------------------------------
_ce1            |
 lnaturalfrozen |          1          .        .       .            .           .
 lGermanyExport |         -1          .        .       .            .           .
         _trend |   .0037267   .0013527     2.76   0.006     .0010755    .0063779
          _cons |   -1.39715          .        .       .            .           .
---------------------------------------------------------------------------------
LR test of identifying restrictions: chi2(1) = 2.442       Prob > chi2 = 0.118

41 . test ([D_naturalfrozen]: L._ce1)
equation D_naturalfrozen not found
r(303);

42 . test ([D_lnaturalfrozen]: L._ce1)

 ( 1)  [D_lnaturalfrozen]L._ce1 = 0

           chi2(  1) =    9.99
         Prob > chi2 =    0.0016

43 . test ([D_lGermanyExport]: L._ce1)

 ( 1)  [D_lGermanyExport]L._ce1 = 0

           chi2(  1) =    3.60
         Prob > chi2 =    0.0579

44 . constraint 1 _b[lnaturalfreshpp] = 1

45 .
46 . constraint 2 _b[lGermanyExport] = -1

47 .
48 . vec lnaturalfreshpp lGermanyExport, trend(rtrend) rank(1) lags(3) bconstraint(1/2)

Iteration 1:     log likelihood = 260.34828
Iteration 2:     log likelihood = 260.38625
Iteration 3:     log likelihood = 260.38626
Iteration 4:     log likelihood = 260.38626
Iteration 5:     log likelihood = 260.38626

Vector error-correction model

Sample:  2009m4 - 2019m12                       Number of obs     =        129
                                                AIC               =  -3.835446
Log likelihood =  260.3863                      HQIC              =  -3.718345
Det(Sigma_ml)  =  .0000605                      SBIC              =  -3.547248
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lnaturalfres~p	**6**	**.111674**	**0.3629**	**70.06669**	**0.0000**
D_lGermanyExport	**6**	**.073913**	**0.0987**	**13.46635**	**0.0362**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lnaturalfreshpp						
_ce1						
L1.	**-.0851751**	**.0542354**	**-1.57**	**0.116**	**-.1914747**	**.0211244**
lnaturalfreshpp						
LD.	**-.537135**	**.0860465**	**-6.24**	**0.000**	**-.705783**	**-.3684869**
L2D.	**-.4128211**	**.0813206**	**-5.08**	**0.000**	**-.5722065**	**-.2534358**
lGermanyExport						
LD.	**-.2045421**	**.1346**	**-1.52**	**0.129**	**-.4683533**	**.0592691**
L2D.	**-.1321855**	**.1391767**	**-0.95**	**0.342**	**-.4049669**	**.1405958**
_cons	**.0080769**	**.009906**	**0.82**	**0.415**	**-.0113385**	**.0274923**
D_lGermanyExport						
_ce1						
L1.	**.1047109**	**.0358965**	**2.92**	**0.004**	**.0343551**	**.1750667**
lnaturalfreshpp						
LD.	**-.100656**	**.056951**	**-1.77**	**0.077**	**-.212278**	**.010966**
L2D.	**-.0296435**	**.0538231**	**-0.55**	**0.582**	**-.1351348**	**.0758479**
lGermanyExport						
LD.	**.1965398**	**.0890868**	**2.21**	**0.027**	**.0219328**	**.3711467**
L2D.	**.0723442**	**.092116**	**0.79**	**0.432**	**-.1081998**	**.2528881**
_cons	**.00657**	**.0065564**	**1.00**	**0.316**	**-.0062803**	**.0194204**

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	**0**	.	.

Identification: beta is overidentified

(1) **[_ce1]lnaturalfreshpp = 1**
(2) **[_ce1]lGermanyExport = -1**

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lnaturalfreshpp	**1**	.	.	.	.	.
lGermanyExport	**-1**	.	.	.	.	.
_trend	**.003012**	**.0013695**	**2.20**	**0.028**	**.0003279**	**.0056961**
_cons	**-1.42305**	.	.	.	.	.

LR test of identifying restrictions: chi2(**1**) = **4.263** Prob > chi2 = **0.039**

49 . test ([D_lnaturalfreshpp]: L._ce1)

(1) **[D_lnaturalfreshpp]L._ce1 = 0**

chi2(1) = **2.47**
Prob > chi2 = **0.1163**

```
50 . test ([D_lGermanyExport]: L._ce1)

    ( 1)  [D_lGermanyExport]L._ce1 = 0

              chi2(  1) =    8.51
            Prob > chi2 =    0.0035

51 . constraint 1 _b[lnaturalfreshnpp] = 1

52 .
53 . constraint 2 _b[lGermanyExport] = -1

54 .
55 . vec lnaturalfreshnpp lGermanyExport, trend(rtrend) rank(1) lags(1) bconstraint(1/2)

   Iteration 1:     log likelihood = 334.70455
   Iteration 2:     log likelihood = 334.71555
   Iteration 3:     log likelihood = 334.71555
   Iteration 4:     log likelihood = 334.71555

   Vector error-correction model

   Sample:  2009m2 - 2019m12                        Number of obs     =        131
                                                    AIC               =  -5.033825
   Log likelihood =  334.7156                       HQIC              =  -4.989233
   Det(Sigma_ml)  =  .0000207                       SBIC              =  -4.924085

   Equation           Parms      RMSE     R-sq      chi2     P>chi2
   ----------------------------------------------------------------
   D_lnaturalfres~p      2     .063815   0.1163   16.9696   0.0002
   D_lGermanyExport      2     .075348   0.0207   2.728034  0.2556
   ----------------------------------------------------------------

   ------------------------------------------------------------------------------------
                      |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
   -------------------+----------------------------------------------------------------
   D_lnaturalfreshnpp |
                 _ce1 |
                  L1. |  -.1775706   .0437472    -4.06   0.000    -.2633135   -.0918277
                      |
                _cons |   .0026756    .005584     0.48   0.632    -.0082688      .01362
   -------------------+----------------------------------------------------------------
   D_lGermanyExport   |
                 _ce1 |
                  L1. |   .0688853   .0516532     1.33   0.182    -.0323531    .1701237
                      |
                _cons |   .0068971   .0065931     1.05   0.296    -.0060252    .0198194
   ------------------------------------------------------------------------------------

   Cointegrating equations

   Equation           Parms    chi2     P>chi2
   -------------------------------------------
   _ce1                  0         .         .
   -------------------------------------------

   Identification:  beta is overidentified

    ( 1)  [_ce1]lnaturalfreshnpp = 1
    ( 2)  [_ce1]lGermanyExport = -1
   ----------------------------------------------------------------------------------
               beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
   -----------------+----------------------------------------------------------------
   _ce1             |
   lnaturalfreshnpp |          1          .        .       .            .           .
     lGermanyExport |         -1          .        .       .            .           .
             _trend |   .0029258   .0007021     4.17   0.000     .0015496    .0043019
              _cons |  -1.785321          .        .       .            .           .
   ----------------------------------------------------------------------------------
   LR test of identifying restrictions: chi2(1) = 50.74       Prob > chi2 = 0.000
```

```
56 . test ([D_lnaturalfreshnpp]: L._ce1)

 ( 1)  [D_lnaturalfreshnpp]L._ce1 = 0

           chi2(  1) =   16.48
         Prob > chi2 =    0.0000

57 . test ([D_lGermanyExport]: L._ce1)

 ( 1)  [D_lGermanyExport]L._ce1 = 0

           chi2(  1) =    1.78
         Prob > chi2 =    0.1823

58 .
```

Statistics/Data Analysis

User: 1

1 . vec lsmokedfreshpp lGermanyExport, trend(rtrend) rank(1) lags(2)

Vector error-correction model

Sample:	**2009m3 - 2019m12**	Number of obs	=	**130**
		AIC	=	**-6.981902**
Log likelihood =	**463.8236**	HQIC	=	**-6.892273**
Det(Sigma_ml) =	**2.73e-06**	SBIC	=	**-6.761322**

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lsmokedfreshpp	4	.023121	0.1874	28.83382	0.0000
D_lGermanyExport	4	.074289	0.0695	9.337304	0.0532

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lsmokedfreshpp						
_ce1 L1.	-.09268	.0203788	-4.55	0.000	-.1326216	-.0527383
lsmokedfreshpp LD.	-.2085167	.0816386	-2.55	0.011	-.3685253	-.0485081
lGermanyExport LD.	-.0590344	.0289233	-2.04	0.041	-.115723	-.0023458
_cons	.0059031	.0020906	2.82	0.005	.0018055	.0100007
D_lGermanyExport						
_ce1 L1.	.1432288	.0654796	2.19	0.029	.0148912	.2715664
lsmokedfreshpp LD.	-.1226497	.262315	-0.47	0.640	-.6367775	.3914782
lGermanyExport LD.	.2236542	.0929342	2.41	0.016	.0415066	.4058018
_cons	.0038198	.0067175	0.57	0.570	-.0093463	.0169858

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	1	33.17567	0.0000

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lsmokedfreshpp	1	.	.	.	.	.
lGermanyExport	-.673085	.1168584	-5.76	0.000	-.9021233	-.4440467
_trend	.0008606	.0009245	0.93	0.352	-.0009513	.0026726
_cons	-2.041291	.	.	.	.	.

2 . vec lsmokedfreshnpp lGermanyExport, trend(rtrend) rank(1) lags(1)

Vector error-correction model

Sample:	**2009m2 - 2019m12**	Number of obs =	**131**
		AIC =	**-4.33024**
Log likelihood =	**289.6307**	HQIC =	**-4.276729**
Det(Sigma_ml) =	**.0000412**	SBIC =	**-4.198552**

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lsmokedfresh~p	**2**	**.086076**	**0.3823**	**79.22144**	**0.0000**
D_lGermanyExport	**2**	**.075707**	**0.0114**	**1.470498**	**0.4794**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lsmokedfreshnpp						
_ce1 L1.	**-.75807**	**.0851786**	**-8.90**	**0.000**	**-.9250171**	**-.591123**
_cons	**-.0004672**	**.00755**	**-0.06**	**0.951**	**-.015265**	**.0143306**
D_lGermanyExport						
_ce1 L1.	**-.054913**	**.0749176**	**-0.73**	**0.464**	**-.2017488**	**.0919227**
_cons	**.0064492**	**.0066405**	**0.97**	**0.331**	**-.0065659**	**.0194644**

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	**1**	**.0548801**	**0.8148**

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lsmokedfreshnpp	**1**	.	.	.	.	.
lGermanyExport	**-.013875**	**.0592278**	**-0.23**	**0.815**	**-.1299594**	**.1022094**
_trend	**-.0000706**	**.0004721**	**-0.15**	**0.881**	**-.0009959**	**.0008547**
_cons	**-2.789062**	.	.	.	.	.

3 . vec lpreparedfrozen lGermanyExport, trend(rtrend) rank(1) lags(4)

Vector error-correction model

Sample:	**2009m5 - 2019m12**	Number of obs =	**128**
		AIC =	**-3.587967**
Log likelihood =	**247.6299**	HQIC =	**-3.425012**
Det(Sigma_ml) =	**.0000716**	SBIC =	**-3.186901**

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lpreparedfro~n	**8**	**.123833**	**0.3009**	**51.21143**	**0.0000**
D_lGermanyExport	**8**	**.072916**	**0.1429**	**19.83702**	**0.0110**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lpreparedfrozen						
_ce1						
L1.	-.6329572	.120564	-5.25	0.000	-.8692583	-.3966562
lpreparedfrozen						
LD.	.0833932	.1152199	0.72	0.469	-.1424337	.3092202
L2D.	.1968275	.1065744	1.85	0.065	-.0120545	.4057095
L3D.	.1440125	.0933455	1.54	0.123	-.0389414	.3269664
lGermanyExport						
LD.	-.1800589	.1493529	-1.21	0.228	-.4727851	.1126673
L2D.	.0023184	.1515708	0.02	0.988	-.2947549	.2993917
L3D.	.2627629	.1496517	1.76	0.079	-.030549	.5560749
_cons	-.0008391	.011124	-0.08	0.940	-.0226418	.0209636
D_lGermanyExport						
_ce1						
L1.	-.0809979	.070991	-1.14	0.254	-.2201376	.0581419
lpreparedfrozen						
LD.	.0251264	.0678443	0.37	0.711	-.107846	.1580987
L2D.	-.0853455	.0627536	-1.36	0.174	-.2083402	.0376493
L3D.	-.1236438	.0549641	-2.25	0.024	-.2313714	-.0159161
lGermanyExport						
LD.	.1157394	.0879425	1.32	0.188	-.0566249	.2881036
L2D.	.0423094	.0892485	0.47	0.635	-.1326145	.2172333
L3D.	-.1249374	.0881185	-1.42	0.156	-.2976465	.0477717
_cons	.006557	.0065501	1.00	0.317	-.0062809	.019395

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	1	4.418502	0.0356

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lpreparedfrozen	1	.	.	.	.	.
lGermanyExport	.2357362	.1121473	2.10	0.036	.0159316	.4555408
_trend	-.0048932	.0008876	-5.51	0.000	-.0066328	-.0031535
_cons	-2.418778	.	.	.	.	.

4 . vec lpreparedfreshpp lGermanyExport, trend(rtrend) rank(1) lags(3)

Vector error-correction model

Sample:	2009m4 - 2019m12	Number of obs	=	129
		AIC	=	-3.541464
Log likelihood =	242.4244	HQIC	=	-3.415355
Det(Sigma_ml) =	.0000799	SBIC	=	-3.231097

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lpreparedfre~p	6	.129434	0.2343	37.3255	0.0000
D_lGermanyExport	6	.073186	0.1163	16.0577	0.0134

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lpreparedfreshpp						
_ce1						
L1.	-.340412	.0913343	-3.73	0.000	-.5194239	-.1614001
lpreparedfreshpp						
LD.	-.11224	.1031772	-1.09	0.277	-.3144636	.0899836
L2D.	.0128726	.0913454	0.14	0.888	-.166161	.1919063
lGermanyExport						
LD.	-.2667662	.1571302	-1.70	0.090	-.5747358	.0412033
L2D.	-.2662559	.1604395	-1.66	0.097	-.5807115	.0481997
_cons	.0013419	.0117148	0.11	0.909	-.0216188	.0243025
D_lGermanyExport						
_ce1						
L1.	.0729539	.0516435	1.41	0.158	-.0282656	.1741734
lpreparedfreshpp						
LD.	.0683803	.0583399	1.17	0.241	-.0459639	.1827245
L2D.	.092624	.0516498	1.79	0.073	-.0086077	.1938558
lGermanyExport						
LD.	.1028368	.0888468	1.16	0.247	-.0712998	.2769733
L2D.	.0726829	.090718	0.80	0.423	-.1051211	.2504869
_cons	.0062613	.006624	0.95	0.345	-.0067214	.0192441

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	1	1.157045	0.2821

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lpreparedfreshpp	1	.	.	.	.	.
lGermanyExport	-.2032655	.1889681	-1.08	0.282	-.5736361	.1671051
_trend	-.0032184	.0014983	-2.15	0.032	-.006155	-.0002817
_cons	-2.288262	.	.	.	.	.

5 . vec lpreparedfreshnpp lGermanyExport, trend(rtrend) rank(1) lags(1)

Vector error-correction model

Sample: **2009m2 - 2019m12**

		Number of obs	= **131**
		AIC	= **-4.056763**
Log likelihood =	**271.718**	HQIC	= **-4.003252**
Det(Sigma_ml) =	**.0000541**	SBIC	= **-3.925075**

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lpreparedfre~p	2	.102449	0.3674	74.33646	0.0000
D_lGermanyExport	2	.075337	0.0210	2.745665	0.2534

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lpreparedfreshnpp						
_ce1						
L1.	-.7253187	.084126	-8.62	0.000	-.8902027	-.5604347
_cons	-.0007218	.0089866	-0.08	0.936	-.0183352	.0168917
D_lGermanyExport						
_ce1						
L1.	-.0830728	.0618632	-1.34	0.179	-.2043225	.0381769
_cons	.0063019	.0066084	0.95	0.340	-.0066504	.0192541

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	1	.669413	0.4133

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lpreparedfreshnpp	1	.	.	.	.	.
lGermanyExport	-.0557847	.0681817	-0.82	0.413	-.1894183	.077849
_trend	.0004052	.0005435	0.75	0.456	-.00066	.0014703
_cons	-2.731254	.	.	.	.	.

```
6 . vec lnaturalfrozen lGermanyExport, trend(rtrend) rank(1) lags(3)
```

Vector error-correction model

Sample:	**2009m4 - 2019m12**	Number of obs =	**129**
		AIC =	**-6.108943**
Log likelihood =	**408.0268**	HQIC =	**-5.982834**
Det(Sigma_ml) =	**6.13e-06**	SBIC =	**-5.798575**

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lnaturalfrozen	6	.036437	0.1902	28.66293	0.0001
D_lGermanyExport	6	.071839	0.1486	21.28672	0.0016

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lnaturalfrozen						
_ce1						
L1.	.0070169	.0024297	2.89	0.004	.0022548	.011779
lnaturalfrozen						
LD.	-.359611	.0881187	-4.08	0.000	-.5323205	-.1869014
L2D.	-.2448519	.0872729	-2.81	0.005	-.4159037	-.0738001
lGermanyExport						
LD.	.0471656	.0446617	1.06	0.291	-.0403698	.134701
L2D.	.0114463	.0460744	0.25	0.804	-.0788578	.1017504
_cons	.0064239	.0033631	1.91	0.056	-.0001677	.0130156
D_lGermanyExport						
_ce1						
L1.	-.0136174	.0047903	-2.84	0.004	-.0230063	-.0042286
lnaturalfrozen						
LD.	-.0444007	.1737327	-0.26	0.798	-.3849106	.2961092

L2D.	-.3738234	.1720652	-2.17	0.030	-.711065	-.0365818
lGermanyExport						
LD.	.1937741	.088054	2.20	0.028	.0211914	.3663568
L2D.	.0815036	.0908391	0.90	0.370	-.0965378	.2595451
_cons	.0033102	.0066307	0.50	0.618	-.0096857	.016306

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	1	14.71384	0.0001

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
_ce1						
lnaturalfrozen	1	.	.	.	.	.
lGermanyExport	8.732156	2.276451	3.84	0.000	4.270393	13.19392
_trend	-.0605607	.0178304	-3.40	0.001	-.0955077	-.0256138
_cons	-10.45208	.	.	.	.	.

7 . vec lnaturalfreshpp lGermanyExport, trend(rtrend) rank(1) lags(3)

Vector error-correction model

Sample:	2009m4 - 2019m12	Number of obs =	129
		AIC =	-3.852992
Log likelihood =	262.518	HQIC =	-3.726883
Det(Sigma_ml) =	.0000585	SBIC =	-3.542624

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lnaturalfres~p	6	.105863	0.4275	91.09798	0.0000
D_lGermanyExport	6	.076406	0.0368	4.666843	0.5872

	Coef.	Std. Err.	z	P>|z|	[95% Conf. Interval]	
D_lnaturalfreshpp						
_ce1						
L1.	-.5010429	.1234084	-4.06	0.000	-.7429189	-.2591669
lnaturalfreshpp						
LD.	-.2703585	.1089936	-2.48	0.013	-.483982	-.056735
L2D.	-.2697444	.0864453	-3.12	0.002	-.4391741	-.1003146
lGermanyExport						
LD.	-.1385566	.1273043	-1.09	0.276	-.3880684	.1109551
L2D.	-.0793429	.1287031	-0.62	0.538	-.3315964	.1729105
_cons	.0002697	.0096531	0.03	0.978	-.0186501	.0191895
D_lGermanyExport						
_ce1						
L1.	.0227973	.0890698	0.26	0.798	-.1517762	.1973709
lnaturalfreshpp						
LD.	-.050598	.0786659	-0.64	0.520	-.2047803	.1035844
L2D.	.0026537	.0623917	0.04	0.966	-.1196319	.1249393
lGermanyExport						
LD.	.1600467	.0918816	1.74	0.082	-.0200379	.3401314
L2D.	.0086383	.0928912	0.09	0.926	-.1734251	.1907018
_cons	.0059278	.0069671	0.85	0.395	-.0077275	.0195831

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	**1**	**.0386138**	**0.8442**

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lnaturalfreshpp	**1**	.	.	.	.	.
lGermanyExport	**-.0228104**	**.1160809**	**-0.20**	**0.844**	**-.2503247**	**.204704**
_trend	**-.003907**	**.0009212**	**-4.24**	**0.000**	**-.0057124**	**-.0021015**
_cons	**-2.279859**	.	.	.	.	.

8 . vec lnaturalfreshnpp lGermanyExport, trend(rtrend) rank(1) lags(1)

Vector error-correction model

Sample:	**2009m2 - 2019m12**	Number of obs =	**131**
		AIC =	**-5.40588**
Log likelihood =	**360.0851**	HQIC =	**-5.352369**
Det(Sigma_ml) =	**.000014**	SBIC =	**-5.274191**

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lnaturalfres~p	**2**	**.051492**	**0.4246**	**94.45741**	**0.0000**
D_lGermanyExport	**2**	**.074636**	**0.0391**	**5.213085**	**0.0738**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lnaturalfreshnpp						
_ce1						
L1.	**-.7727991**	**.0798337**	**-9.68**	**0.000**	**-.9292702**	**-.6163279**
_cons	**-.0014673**	**.0045506**	**-0.32**	**0.747**	**-.0103863**	**.0074517**
D_lGermanyExport						
_ce1						
L1.	**-.2386337**	**.1157153**	**-2.06**	**0.039**	**-.4654316**	**-.0118359**
_cons	**.0047517**	**.0065959**	**0.72**	**0.471**	**-.008176**	**.0176794**

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	**1**	**95.39631**	**0.0000**

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lnaturalfreshnpp	**1**	.	.	.	.	.
lGermanyExport	**-.3397914**	**.0347894**	**-9.77**	**0.000**	**-.4079774**	**-.2716055**
_trend	**-.0015525**	**.0002773**	**-5.60**	**0.000**	**-.002096**	**-.001009**
_cons	**-2.366775**	.	.	.	.	.

9 .

SPAIN

Statistics/Data Analysis

User: 1

1 . varsoc lSpainExport

Selection-order criteria
Sample: **2015m5 - 2019m12** Number of obs = **56**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	24.3638				.025418	-.83442	-.820398	-.798253
1	66.5013	84.275	1	0.000	.005849	-2.30362	-2.27558	-2.23129*
2	68.5114	4.0201*	1	0.045	.005642*	-2.33969*	-2.29763*	-2.23119
3	69.2786	1.5345	1	0.215	.00569	-2.33138	-2.27529	-2.18671
4	69.4773	.39738	1	0.528	.005857	-2.30276	-2.23265	-2.12193

Endogenous: lSpainExport
Exogenous: _cons

2 . varsoc lsmokedfrozen

Selection-order criteria
Sample: **2015m5 - 2018m12, but with gaps** Number of obs = **19**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-10.1669				.189699*	1.17546*	1.18388*	1.22517*
1	-10.1649	.00405	1	0.949	.210856	1.28051	1.29734	1.37993
2	-10.0871	.15562	1	0.693	.232788	1.37759	1.40282	1.52671
3	-9.22188	1.7304	1	0.188	.236997	1.39178	1.42543	1.59061
4	-8.8224	.79895	1	0.371	.254054	1.45499	1.49705	1.70353

Endogenous: lsmokedfrozen
Exogenous: _cons

3 . varsoc lsmokedfreshpp

Selection-order criteria
Sample: **2017m9 - 2019m12** Number of obs = **28**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	53.6424				.001363	-3.76017	-3.74563	-3.71259
1	56.9943	6.7038	1	0.010	.001153	-3.92816	-3.89907	-3.83301
2	59.2257	4.4629*	1	0.035	.001056*	-4.01612*	-3.97249*	-3.87339*
3	59.8229	1.1943	1	0.274	.001088	-3.98735	-3.92917	-3.79703
4	59.8428	.03983	1	0.842	.001169	-3.91734	-3.84462	-3.67945

Endogenous: lsmokedfreshpp
Exogenous: _cons

4 . varsoc lsmokedfreshnpp

Selection-order criteria
Sample: **2015m5 - 2019m12** Number of obs = **56**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	69.3188				.005103	-2.43996	-2.42593	-2.40379
1	95.3219	52.006*	1	0.000	.00209	-3.33293	-3.30488	-3.26059*
2	96.8185	2.9932	1	0.084	.002053*	-3.35066*	-3.3086*	-3.24216
3	97.2603	.88365	1	0.347	.002095	-3.33073	-3.27464	-3.18606
4	98.166	1.8112	1	0.178	.002102	-3.32736	-3.25725	-3.14652

Endogenous: lsmokedfreshnpp
Exogenous: _cons

5 . varsoc lsalteddried

Selection-order criteria
Sample: **2015m5 - 2019m12** Number of obs = **56**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-31.002				.18361*	1.14293*	1.15695*	1.1791*
1	-30.9993	.00548	1	0.941	.190272	1.17855	1.20659	1.25088
2	-30.2105	1.5775	1	0.209	.191727	1.18609	1.22816	1.29459
3	-29.8996	.62188	1	0.430	.196531	1.2107	1.26679	1.35537
4	-29.3507	1.0978	1	0.295	.19977	1.22681	1.29692	1.40764

Endogenous: lsalteddried
Exogenous: _cons

6 . varsoc lpreparedfrozen

Selection-order criteria
Sample: **2015m5 - 2019m12** Number of obs = **56**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-.180735				.061072	.042169	.056191	.078336
1	5.0486	10.459	1	0.001	.052511	-.108879	-.080835	-.036545
2	7.21607	4.3349*	1	0.037	.050371	-.150574	-.108508*	-.042073*
3	7.92512	1.4181	1	0.234	.050904	-.140183	-.084095	.004485
4	9.47612	3.102	1	0.078	.049924*	-.159861*	-.089752	.020974

Endogenous: lpreparedfrozen
Exogenous: _cons

7 . varsoc lpreparedfresh

Selection-order criteria
Sample: **2015m5 - 2019m12** Number of obs = **56**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	24.261				.025512	-.830748	-.816727	-.794581
1	87.3009	126.08*	1	0.000	.002783*	-3.04646*	-3.01842*	-2.97413*
2	87.4369	.27187	1	0.602	.00287	-3.0156	-2.97354	-2.9071
3	87.7931	.71251	1	0.399	.002937	-2.99261	-2.93652	-2.84794
4	88.2153	.84436	1	0.358	.002999	-2.97198	-2.90187	-2.79114

Endogenous: lpreparedfresh
Exogenous: _cons

8 . varsoc lnaturalfrozen

Selection-order criteria
Sample: **2015m5 - 2019m12** Number of obs = **56**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	59.4967				.007248	-2.08917	-2.07515	-2.053
1	78.0874	37.181	1	0.000	.003867	-2.71741	-2.68936	-2.64507
2	82.4021	8.6294*	1	0.003	.003436*	-2.83579*	-2.79373*	-2.72729*
3	82.6529	.50157	1	0.479	.003529	-2.80903	-2.75295	-2.66437
4	83.2864	1.2669	1	0.260	.003577	-2.79594	-2.72583	-2.61511

Endogenous: lnaturalfrozen
Exogenous: _cons

```
 9 . varsoc lnaturalfreshpp

     Selection-order criteria
     Sample:  2015m5 - 2019m12                    Number of obs      =        56
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	49.7807				.010254	-1.74217	-1.72815	-1.706
1	64.8847	30.208	1	0.000	.006197	-2.24588	-2.21784	-2.17355*
2	65.4159	1.0623	1	0.303	.006302	-2.22914	-2.18707	-2.12064
3	67.4805	4.1292*	1	0.042	.006068	-2.26716	-2.21107	-2.12249
4	69.1	3.239	1	0.072	.005936*	-2.28929*	-2.21918*	-2.10845

```
     Endogenous:  lnaturalfreshpp
      Exogenous:  _cons

10 . varsoc lnaturalfreshnpp

     Selection-order criteria
     Sample:  2015m5 - 2019m12                    Number of obs      =        56
```

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	51.209				.009745	-1.79318	-1.77916	-1.75701
1	105.315	108.21	1	0.000	.001462	-3.68981	-3.66176	-3.61747
2	108.223	5.8158*	1	0.016	.001366*	-3.75795*	-3.71588*	-3.64945*
3	108.279	.1123	1	0.738	.001413	-3.72424	-3.66815	-3.57957
4	108.307	.05643	1	0.812	.001463	-3.68953	-3.61942	-3.5087

```
     Endogenous:  lnaturalfreshnpp
      Exogenous:  _cons

11 .
```

```
  ___  ____  ____  ____  ____(R)
 /__    /   ____/   /   ____/
___/   /   /___/   /   /___/
  Statistics/Data Analysis
```

User: 1

1 . varsoc d.lSpainExport

Selection-order criteria
Sample: **2015m6 - 2019m12** Number of obs = **55**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	62.1995				.006325	-2.22544	-2.21132*	-2.18894*
1	63.172	1.945	1	0.163	.006331	-2.22444	-2.19621	-2.15144
2	64.6931	3.0423	1	0.081	.006213*	-2.24339*	-2.20105	-2.1339
3	65.2683	1.1504	1	0.283	.00631	-2.22794	-2.17148	-2.08195
4	65.7293	.92188	1	0.337	.006437	-2.20834	-2.13777	-2.02585

Endogenous: D.lSpainExport
Exogenous: _cons

2 . varsoc d.lsmokedfrozen

Selection-order criteria
Sample: **2016m12 - 2018m12, but with a gap** Number of obs = **16**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-15.2893				.448633	2.03616	2.03864	2.08445
1	-11.9576	6.6634*	1	0.010	.335592	1.7447	1.74965	1.84128
2	-10.4866	2.942	1	0.086	.31741*	1.68583*	1.69324*	1.83069*
3	-9.52606	1.9211	1	0.166	.321007	1.69076	1.70065	1.8839
4	-9.4707	.11072	1	0.739	.365163	1.80884	1.8212	2.05027

Endogenous: D.lsmokedfrozen
Exogenous: _cons

3 . varsoc d.lsmokedfreshpp

Selection-order criteria
Sample: **2017m10 - 2019m12** Number of obs = **27**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	49.9229				.001562	-3.62392	-3.60964	-3.57592
1	54.6936	9.5414*	1	0.002	.001182	-3.90323	-3.87469	-3.80724*
2	55.9253	2.4634	1	0.117	.001162*	-3.92039*	-3.87758*	-3.77641
3	55.9258	.00107	1	0.974	.001253	-3.84636	-3.78927	-3.65438
4	56.8703	1.8889	1	0.169	.001261	-3.84224	-3.77089	-3.60227

Endogenous: D.lsmokedfreshpp
Exogenous: _cons

4 . varsoc d.lsmokedfreshnpp

Selection-order criteria
Sample: **2015m6 - 2019m12** Number of obs = **55**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	89.7239				.002325	-3.22632	-3.21221	-3.18983
1	92.529	5.6102*	1	0.018	.002177	-3.29196	-3.26374*	-3.21897*
2	93.4809	1.9039	1	0.168	.002181	-3.29022	-3.24787	-3.18072
3	95.087	3.2122	1	0.073	.002134	-3.31226	-3.2558	-3.16627
4	96.1068	2.0395	1	0.153	.002133*	-3.31297*	-3.24241	-3.13049

Endogenous: D.lsmokedfreshnpp
Exogenous: _cons

```
5 . varsoc d.lsalteddried
```

Selection-order criteria
Sample: **2015m6 - 2019m12** Number of obs = **55**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-49.6621				.369496	1.84226	1.85637	1.87875
1	-44.5436	10.237	1	0.001	.318113	1.6925	1.72072	1.76549
2	-37.2246	14.638	1	0.000	.252826	1.46271	1.50505	1.5722
3	-33.6683	7.1127*	1	0.008	.230417	1.36976	1.42621*	1.51574*
4	-32.5584	2.2198	1	0.136	.229555*	1.36576*	1.43633	1.54825

Endogenous: D.lsalteddried
Exogenous: _cons

```
6 . varsoc d.lpreparedfrozen
```

Selection-order criteria
Sample: **2015m6 - 2019m12** Number of obs = **55**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	-5.17987				.073303	.224723	.238836	.26122
1	2.39813	15.156	1	0.000	.05771	-.014477	.01375	.058517
2	4.53514	4.274	1	0.039	.055377	-.055823	-.013482	.053667
3	7.15825	5.2462*	1	0.022	.052211*	-.114846*	-.058391*	.031142*
4	7.22752	.13854	1	0.710	.054021	-.081001	-.010432	.101484

Endogenous: D.lpreparedfrozen
Exogenous: _cons

```
7 . varsoc d.lpreparedfresh
```

Selection-order criteria
Sample: **2015m6 - 2019m12** Number of obs = **55**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	83.8822				.002875*	-3.0139*	-2.99978*	-2.9774*
1	84.2373	.71027	1	0.399	.002943	-2.99045	-2.96222	-2.91745
2	84.9911	1.5077	1	0.219	.00297	-2.9815	-2.93916	-2.87201
3	85.7901	1.5978	1	0.206	.002992	-2.97418	-2.91773	-2.8282
4	86.2231	.86613	1	0.352	.003055	-2.95357	-2.883	-2.77108

Endogenous: D.lpreparedfresh
Exogenous: _cons

```
8 . varsoc d.lnaturalfrozen
```

Selection-order criteria
Sample: **2015m6 - 2019m12** Number of obs = **55**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	72.1625				.004402	-2.58773	-2.57361	-2.55123
1	78.9265	13.528	1	0.000	.00357	-2.79733	-2.7691*	-2.72433*
2	79.6825	1.512	1	0.219	.003602	-2.78845	-2.74611	-2.67896
3	80.6352	1.9055	1	0.167	.003609	-2.78674	-2.73028	-2.64075
4	82.9108	4.5512*	1	0.033	.003446*	-2.83312*	-2.76255	-2.65063

Endogenous: D.lnaturalfrozen
Exogenous: _cons

```
9 . varsoc d.lnaturalfreshpp
```

Selection-order criteria
Sample: **2015m6 - 2019m12** Number of obs = **55**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	57.6429				.007464	-2.05974	-2.04563	-2.02325
1	59.9559	4.626	1	0.031	.007117	-2.10749	-2.07926	-2.03449
2	63.5135	7.1152	1	0.008	.006485	-2.20049	-2.15815	-2.091
3	65.8729	4.7188	1	0.030	.006173	-2.24992	-2.19347	-2.10394
4	70.1085	8.4711*	1	0.004	.005489*	-2.36758*	-2.29701*	-2.1851*

Endogenous: D.lnaturalfreshpp
Exogenous: _cons

```
10 . varsoc d.lnaturalfreshnpp
```

Selection-order criteria
Sample: **2015m6 - 2019m12** Number of obs = **55**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	101.102				.001537	-3.64007	-3.62595	-3.60357*
1	103.014	3.8236	1	0.051	.001487*	-3.67322*	-3.64499*	-3.60023
2	103.035	.04316	1	0.835	.001541	-3.63764	-3.5953	-3.52815
3	103.094	.11794	1	0.731	.001595	-3.60342	-3.54697	-3.45744
4	103.831	1.4732	1	0.225	.00161	-3.59384	-3.52328	-3.41136

Endogenous: D.lnaturalfreshnpp
Exogenous: _cons

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  Statistics/Data Analysis
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User: 1

1 . dfuller lSpainExport, lags(2)

Augmented Dickey-Fuller test for unit root Number of obs = **57**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-2.205**	**-3.570**	**-2.924**	**-2.597**

MacKinnon approximate p-value for Z(t) = **0.2046**

2 . dfuller lsmokedfrozen, lags(0)

Dickey-Fuller test for unit root Number of obs = **37**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-4.979**	**-3.668**	**-2.966**	**-2.616**

MacKinnon approximate p-value for Z(t) = **0.0000**

3 . dfuller lsmokedfreshpp, lags(2)

Augmented Dickey-Fuller test for unit root Number of obs = **29**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-1.928**	**-3.723**	**-2.989**	**-2.625**

MacKinnon approximate p-value for Z(t) = **0.3189**

4 . dfuller lsmokedfreshnpp, lags(2)

Augmented Dickey-Fuller test for unit root Number of obs = **57**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-1.874**	**-3.570**	**-2.924**	**-2.597**

MacKinnon approximate p-value for Z(t) = **0.3443**

5 . dfuller lsalteddried, lags(0)

Dickey-Fuller test for unit root Number of obs = **59**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-7.390**	**-3.567**	**-2.923**	**-2.596**

MacKinnon approximate p-value for Z(t) = **0.0000**

6 . dfuller lpreparedfrozen, lags(4)

Augmented Dickey-Fuller test for unit root Number of obs = **55**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-1.738**	**-3.573**	**-2.926**	**-2.598**

MacKinnon approximate p-value for Z(t) = **0.4117**

7 . dfuller lpreparedfresh, lags(1)

Augmented Dickey-Fuller test for unit root Number of obs = **58**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-1.170**	**-3.569**	**-2.924**	**-2.597**

MacKinnon approximate p-value for Z(t) = **0.6862**

8 . dfuller lnaturalfrozen, lags(2)

Augmented Dickey-Fuller test for unit root Number of obs = **57**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-1.219**	**-3.570**	**-2.924**	**-2.597**

MacKinnon approximate p-value for Z(t) = **0.6655**

9 . dfuller lnaturalfreshpp, lags(4)

Augmented Dickey-Fuller test for unit root Number of obs = **55**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-1.355**	**-3.573**	**-2.926**	**-2.598**

MacKinnon approximate p-value for Z(t) = **0.6038**

10 . dfuller lnaturalfreshnpp, lags(2)

Augmented Dickey-Fuller test for unit root Number of obs = **57**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-2.217**	**-3.570**	**-2.924**	**-2.597**

MacKinnon approximate p-value for Z(t) = **0.2001**

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Statistics/Data Analysis

User: 1

1 . dfuller lSpainExport, lags(2) trend

Augmented Dickey-Fuller test for unit root Number of obs = **57**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-2.313**	**-4.135**	**-3.493**	**-3.176**

MacKinnon approximate p-value for Z(t) = **0.4270**

2 . dfuller lsmokedfrozen, lags(0) trend

Dickey-Fuller test for unit root Number of obs = **37**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-5.976**	**-4.270**	**-3.552**	**-3.211**

MacKinnon approximate p-value for Z(t) = **0.0000**

3 . dfuller lsmokedfreshpp, lags(2) trend

Augmented Dickey-Fuller test for unit root Number of obs = **29**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-2.259**	**-4.343**	**-3.584**	**-3.230**

MacKinnon approximate p-value for Z(t) = **0.4570**

4 . dfuller lsmokedfreshnpp, lags(2) trend

Augmented Dickey-Fuller test for unit root Number of obs = **57**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-2.675**	**-4.135**	**-3.493**	**-3.176**

MacKinnon approximate p-value for Z(t) = **0.2468**

5 . dfuller lsalteddried, lags(0) trend

Dickey-Fuller test for unit root Number of obs = **59**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-7.821**	**-4.130**	**-3.491**	**-3.175**

MacKinnon approximate p-value for Z(t) = **0.0000**

6 . dfuller lpreparedfrozen, lags(4) trend

Augmented Dickey-Fuller test for unit root Number of obs = **55**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-1.389**	**-4.139**	**-3.495**	**-3.177**

MacKinnon approximate p-value for Z(t) = **0.8640**

7 . dfuller lpreparedfresh, lags(1) trend

Augmented Dickey-Fuller test for unit root Number of obs = **58**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-2.423**	**-4.132**	**-3.492**	**-3.175**

MacKinnon approximate p-value for Z(t) = **0.3677**

8 . dfuller lnaturalfrozen, lags(2) trend

Augmented Dickey-Fuller test for unit root Number of obs = **57**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-3.331**	**-4.135**	**-3.493**	**-3.176**

MacKinnon approximate p-value for Z(t) = **0.0613**

9 . dfuller lnaturalfreshpp, lags(4) trend

Augmented Dickey-Fuller test for unit root Number of obs = **55**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-2.485**	**-4.139**	**-3.495**	**-3.177**

MacKinnon approximate p-value for Z(t) = **0.3354**

10 . dfuller lnaturalfreshnpp, lags(2) trend

Augmented Dickey-Fuller test for unit root Number of obs = **57**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-2.013**	**-4.135**	**-3.493**	**-3.176**

MacKinnon approximate p-value for Z(t) = **0.5944**

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  Statistics/Data Analysis

    User: 1
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```
1 . dfuller d.lSpainExport, lags(2)

Augmented Dickey-Fuller test for unit root         Number of obs   =        56

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.937            -3.572            -2.925            -2.598
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

2 . dfuller d.lsmokedfrozen, lags(2)

Augmented Dickey-Fuller test for unit root         Number of obs   =        19

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.957            -3.750            -3.000            -2.630
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

3 . dfuller d.lsmokedfreshpp, lags(2)

Augmented Dickey-Fuller test for unit root         Number of obs   =        28

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.494            -3.730            -2.992            -2.626
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

4 . dfuller d.lsmokedfreshnpp, lags(4)

Augmented Dickey-Fuller test for unit root         Number of obs   =        54

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -4.484            -3.574            -2.927            -2.598
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0002

5 . dfuller d.lsalteddried, lags(4)

Augmented Dickey-Fuller test for unit root         Number of obs   =        54

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.651            -3.574            -2.927            -2.598
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000

6 . dfuller d.lpreparedfrozen, lags(3)

Augmented Dickey-Fuller test for unit root         Number of obs   =        55

                               ---------- Interpolated Dickey-Fuller ---------
                  Test         1% Critical       5% Critical      10% Critical
               Statistic           Value             Value             Value
------------------------------------------------------------------------------
 Z(t)             -5.338            -3.573            -2.926            -2.598
------------------------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000
```

7 . dfuller d.lpreparedfresh, lags(0)

Dickey-Fuller test for unit root Number of obs = **58**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-7.772**	**-3.569**	**-2.924**	**-2.597**

MacKinnon approximate p-value for Z(t) = **0.0000**

8 . dfuller d.lnaturalfrozen, lags(4)

Augmented Dickey-Fuller test for unit root Number of obs = **54**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-4.348**	**-3.574**	**-2.927**	**-2.598**

MacKinnon approximate p-value for Z(t) = **0.0004**

9 . dfuller d.lnaturalfreshpp, lags(4)

Augmented Dickey-Fuller test for unit root Number of obs = **54**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-5.078**	**-3.574**	**-2.927**	**-2.598**

MacKinnon approximate p-value for Z(t) = **0.0000**

10 . dfuller d.lnaturalfreshnpp, lags(1)

Augmented Dickey-Fuller test for unit root Number of obs = **57**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-4.498**	**-3.570**	**-2.924**	**-2.597**

MacKinnon approximate p-value for Z(t) = **0.0002**

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  Statistics/Data Analysis
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User: 1

1 . dfuller d.lSpainExport, lags(2) trend

Augmented Dickey-Fuller test for unit root   Number of obs   =   **56**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-4.996**	**-4.137**	**-3.494**	**-3.176**

MacKinnon approximate p-value for Z(t) = **0.0002**

2 . dfuller d.lsmokedfrozen, lags(2) trend

Augmented Dickey-Fuller test for unit root   Number of obs   =   **19**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-5.736**	**-4.380**	**-3.600**	**-3.240**

MacKinnon approximate p-value for Z(t) = **0.0000**

3 . dfuller d.lsmokedfreshpp, lags(2) trend

Augmented Dickey-Fuller test for unit root   Number of obs   =   **28**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-5.421**	**-4.352**	**-3.588**	**-3.233**

MacKinnon approximate p-value for Z(t) = **0.0000**

4 . dfuller d.lsmokedfreshnpp, lags(4) trend

Augmented Dickey-Fuller test for unit root   Number of obs   =   **54**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-4.536**	**-4.141**	**-3.496**	**-3.178**

MacKinnon approximate p-value for Z(t) = **0.0013**

5 . dfuller d.lsalteddried, lags(4) trend

Augmented Dickey-Fuller test for unit root   Number of obs   =   **54**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-5.592**	**-4.141**	**-3.496**	**-3.178**

MacKinnon approximate p-value for Z(t) = **0.0000**

6 . dfuller d.lpreparedfrozen, lags(3) trend

Augmented Dickey-Fuller test for unit root   Number of obs   =   **55**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-5.502**	**-4.139**	**-3.495**	**-3.177**

MacKinnon approximate p-value for Z(t) = **0.0000**

7 . dfuller d.lpreparedfresh, lags(0) trend

Dickey-Fuller test for unit root Number of obs = **58**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-7.693**	**-4.132**	**-3.492**	**-3.175**

MacKinnon approximate p-value for Z(t) = **0.0000**

8 . dfuller d.lnaturalfrozen, lags(4) trend

Augmented Dickey-Fuller test for unit root Number of obs = **54**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-4.306**	**-4.141**	**-3.496**	**-3.178**

MacKinnon approximate p-value for Z(t) = **0.0031**

9 . dfuller d.lnaturalfreshpp, lags(4) trend

Augmented Dickey-Fuller test for unit root Number of obs = **54**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-5.067**	**-4.141**	**-3.496**	**-3.178**

MacKinnon approximate p-value for Z(t) = **0.0002**

10 . dfuller d.lnaturalfreshnpp, lags(1) trend

Augmented Dickey-Fuller test for unit root Number of obs = **57**

	Test Statistic	Interpolated Dickey-Fuller 1% Critical Value	5% Critical Value	10% Critical Value
Z(t)	**-4.570**	**-4.135**	**-3.493**	**-3.176**

MacKinnon approximate p-value for Z(t) = **0.0012**

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  Statistics/Data Analysis
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User: 1

1 . reg lsmokedfreshpp lSpainExport

Source	SS	df	MS			
				Number of obs	=	32
				F(1, 30)	=	2.52
Model	.082477097	1	.082477097	Prob > F	=	0.1231
Residual	.98314473	30	.032771491	R-squared	=	0.0774
				Adj R-squared	=	0.0466
Total	1.06562183	31	.034374898	Root MSE	=	.18103

lsmokedf~hpp	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lSpainExport	-.5275263	.3325259	-1.59	0.123	-1.206635	.1515823
_cons	4.274775	.5512469	7.75	0.000	3.148979	5.400571

2 . reg lsmokedfreshnpp lSpainExport

Source	SS	df	MS			
				Number of obs	=	60
				F(1, 58)	=	53.34
Model	.149113127	1	.149113127	Prob > F	=	0.0000
Residual	.162146257	58	.002795625	R-squared	=	0.4791
				Adj R-squared	=	0.4701
Total	.311259383	59	.005275583	Root MSE	=	.05287

lsmokedf~npp	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lSpainExport	.2884064	.0394899	7.30	0.000	.2093587	.3674541
_cons	2.68488	.0632524	42.45	0.000	2.558267	2.811493

3 . reg lpreparedfrozen lSpainExport

Source	SS	df	MS			
				Number of obs	=	60
				F(1, 58)	=	14.49
Model	.729918621	1	.729918621	Prob > F	=	0.0003
Residual	2.92119725	58	.05036547	R-squared	=	0.1999
				Adj R-squared	=	0.1861
Total	3.65111587	59	.06188332	Root MSE	=	.22442

lpreparedf~n	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lSpainExport	.6380934	.1676152	3.81	0.000	.302575	.9736117
_cons	1.639251	.2684749	6.11	0.000	1.10184	2.176662

4 . reg lpreparedfresh lSpainExport

Source	SS	df	MS			
				Number of obs	=	60
				F(1, 58)	=	34.44
Model	.561160541	1	.561160541	Prob > F	=	0.0000
Residual	.945155355	58	.016295782	R-squared	=	0.3725
				Adj R-squared	=	0.3617
Total	1.5063159	59	.025530778	Root MSE	=	.12765

lpreparedf~h	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lSpainExport	.5594877	.0953421	5.87	0.000	.3686398	.7503356
_cons	2.472725	.1527126	16.19	0.000	2.167037	2.778412

```
5 . reg lnaturalfrozen lSpainExport

      Source |       SS           df       MS      Number of obs   =        60
-------------+----------------------------------   F(1, 58)        =     15.25
       Model |  .098649085         1  .098649085   Prob > F        =    0.0002
    Residual |  .375092709        58  .006467116   R-squared       =    0.2082
-------------+----------------------------------   Adj R-squared   =    0.1946
       Total |  .473741794        59  .008029522   Root MSE        =    .08042

------------------------------------------------------------------------------
lnaturalfr~n |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
lSpainExport |   .2345814   .0600624     3.91   0.000     .1143535    .3548092
       _cons |   2.382526   .0962039    24.77   0.000     2.189953    2.575099
------------------------------------------------------------------------------

6 . reg lnaturalfreshpp lSpainExport

      Source |       SS           df       MS      Number of obs   =        60
-------------+----------------------------------   F(1, 58)        =     15.21
       Model |  .136652193         1  .136652193   Prob > F        =    0.0003
    Residual |  .521147038        58  .008985294   R-squared       =    0.2077
-------------+----------------------------------   Adj R-squared   =    0.1941
       Total |  .657799231        59   .01114914   Root MSE        =    .09479

------------------------------------------------------------------------------
lnatural~hpp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
lSpainExport |   .2760929   .0707967     3.90   0.000     .1343779     .417808
       _cons |    2.17036   .1133975    19.14   0.000     1.943371     2.39735
------------------------------------------------------------------------------

7 . reg lnaturalfreshnpp lSpainExport

      Source |       SS           df       MS      Number of obs   =        60
-------------+----------------------------------   F(1, 58)        =    266.84
       Model |  .507669635         1  .507669635   Prob > F        =    0.0000
    Residual |  .110346628        58  .001902528   R-squared       =    0.8215
-------------+----------------------------------   Adj R-squared   =    0.8184
       Total |  .618016264        59  .010474852   Root MSE        =    .04362

------------------------------------------------------------------------------
lnatural~npp |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
lSpainExport |   .5321543   .0325771    16.34   0.000     .4669442    .5973645
       _cons |   1.490887   .0521798    28.57   0.000     1.386437    1.595336
------------------------------------------------------------------------------

8 .
```

```
  ___  ____  ____  ____  ____(R)
 /__    /   ____/   /   ____/
___/   /   /___/   /   /___/
  Statistics/Data Analysis

     User: 1
```

1 . varsoc lsmokedfreshpp lSpainExport

Selection-order criteria
Sample: **2017m9 - 2019m12** Number of obs = **28**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	80.847				.000012	-5.63193	-5.60284	-5.53677
1	90.2236	18.753	4	0.001	8.4e-06	-6.01597	-5.9287	-5.7305*
2	95.0651	9.683*	4	0.046	7.9e-06*	-6.07608*	-5.93063*	-5.60029
3	98.0466	5.9629	4	0.202	8.7e-06	-6.00333	-5.79969	-5.33723
4	100.361	4.6296	4	0.327	.00001	-5.88296	-5.62114	-5.02654

Endogenous: lsmokedfreshpp lSpainExport
Exogenous: _cons

2 . varsoc lsmokedfreshnpp lSpainExport

Selection-order criteria
Sample: **2015m5 - 2019m12** Number of obs = **56**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	108.624				.000076	-3.808	-3.77996	-3.73567
1	165.612	113.98	4	0.000	.000011	-5.70044	-5.61631*	-5.48344*
2	170.386	9.5477*	4	0.049	.000011*	-5.72808*	-5.58786	-5.36641
3	171.934	3.0957	4	0.542	.000012	-5.6405	-5.44419	-5.13416
4	172.98	2.0918	4	0.719	.000014	-5.53499	-5.2826	-4.88399

Endogenous: lsmokedfreshnpp lSpainExport
Exogenous: _cons

3 . varsoc lpreparedfrozen lSpainExport

Selection-order criteria
Sample: **2015m5 - 2019m12** Number of obs = **56**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	28.1403				.001348	-.933583	-.905539	-.861249
1	74.0226	91.764	4	0.000	.000302	-2.42938	-2.34525*	-2.21238*
2	79.484	10.923*	4	0.027	.000287*	-2.48157*	-2.34135	-2.1199
3	81.814	4.6598	4	0.324	.000305	-2.42193	-2.22562	-1.91559
4	84.6853	5.7427	4	0.219	.000319	-2.38162	-2.12923	-1.73061

Endogenous: lpreparedfrozen lSpainExport
Exogenous: _cons

4 . varsoc lpreparedfresh lSpainExport

Selection-order criteria
Sample: **2015m5 - 2019m12** Number of obs = **56**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	59.4982				.00044	-2.05351	-2.02546	-1.98117
1	157.917	196.84	4	0.000	.000015	-5.4256	-5.34147*	-5.2086*
2	163.374	10.915*	4	0.028	.000014*	-5.47766*	-5.33744	-5.11599
3	163.912	1.0755	4	0.898	.000016	-5.354	-5.1577	-4.84767
4	166.674	5.5241	4	0.238	.000017	-5.30979	-5.0574	-4.65878

Endogenous: lpreparedfresh lSpainExport
Exogenous: _cons

5 . varsoc lnaturalfrozen lSpainExport

Selection-order criteria
Sample: **2015m5 - 2019m12** Number of obs = **56**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**87.0863**				**.000164**	**-3.03879**	**-3.01075**	**-2.96646**
1	**145.719**	**117.27**	**4**	**0.000**	**.000023**	**-4.98998**	**-4.90585**	**-4.77298**
2	**154.317**	**17.195***	**4**	**0.002**	**.00002***	**-5.15418***	**-5.01396***	**-4.79251***
3	**156.206**	**3.7774**	**4**	**0.437**	**.000021**	**-5.07878**	**-4.88247**	**-4.57244**
4	**159.553**	**6.694**	**4**	**0.153**	**.000022**	**-5.05546**	**-4.80306**	**-4.40445**

Endogenous: lnaturalfrozen lSpainExport
Exogenous: _cons

6 . varsoc lnaturalfreshpp lSpainExport

Selection-order criteria
Sample: **2015m5 - 2019m12** Number of obs = **56**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**77.4211**				**.000232**	**-2.69361**	**-2.66557**	**-2.62128**
1	**134.418**	**113.99**	**4**	**0.000**	**.000035**	**-4.58637**	**-4.50224***	**-4.36937***
2	**137.439**	**6.0409**	**4**	**0.196**	**.000036**	**-4.55138**	**-4.41116**	**-4.18971**
3	**143.873**	**12.868***	**4**	**0.012**	**.000033***	**-4.63831***	**-4.44201**	**-4.13197**
4	**145.816**	**3.8871**	**4**	**0.421**	**.000036**	**-4.56487**	**-4.31247**	**-3.91386**

Endogenous: lnaturalfreshpp lSpainExport
Exogenous: _cons

7 . varsoc lnaturalfreshnpp lSpainExport

Selection-order criteria
Sample: **2015m5 - 2019m12** Number of obs = **56**

lag	LL	LR	df	p	FPE	AIC	HQIC	SBIC
0	**119.969**				**.000051**	**-4.21316**	**-4.18512**	**-4.14083**
1	**193.254**	**146.57**	**4**	**0.000**	**4.3e-06**	**-6.68763**	**-6.6035**	**-6.47062***
2	**199.556**	**12.605***	**4**	**0.013**	**3.9e-06**	**-6.76986**	**-6.62964***	**-6.40819**
3	**203.972**	**8.832**	**4**	**0.065**	**3.9e-06***	**-6.78472***	**-6.58841**	**-6.27838**
4	**207.625**	**7.3056**	**4**	**0.121**	**3.9e-06**	**-6.77232**	**-6.51992**	**-6.12131**

Endogenous: lnaturalfreshnpp lSpainExport
Exogenous: _cons

8 .

```
                                                          ___  ____  ____  ____  ____(R)
                                                         /__    /   ____/   /   ____/
                                                        ___/   /   /___/   /   /___/
                                                          Statistics/Data Analysis

                                                            User: 1

1 . vecrank lsmokedfreshpp lSpainExport, trend(rtrend) lags(2) ic max

                       Johansen tests for cointegration
Trend: rtrend                                          Number of obs =      30
Sample:  2017m7 - 2019m12                                       Lags =       2
-------------------------------------------------------------------------------
                                                              5%
maximum                                          trace    critical
  rank    parms       LL       eigenvalue   statistic     value
    0       6      87.98029            .      29.4363     25.32
    1      10      96.98804      0.45147      11.4208*    12.25
    2      12     102.69843      0.31661
-------------------------------------------------------------------------------
                                                              5%
maximum                                            max    critical
  rank    parms       LL       eigenvalue   statistic     value
    0       6      87.98029            .      18.0155     18.96
    1      10      96.98804      0.45147      11.4208     12.52
    2      12     102.69843      0.31661
-------------------------------------------------------------------------------
maximum
  rank    parms       LL       eigenvalue     SBIC        HQIC        AIC
    0       6      87.98029                 -5.185113  -5.375702  -5.465353
    1      10      96.98804      0.45147    -5.332137* -5.649784* -5.799203
    2      12     102.69843      0.31661    -5.486083   -5.86726  -6.046562
-------------------------------------------------------------------------------

2 . vecrank lsmokedfreshnpp lSpainExport, trend(rtrend) lags(2) ic max

                       Johansen tests for cointegration
Trend: rtrend                                          Number of obs =      58
Sample:  2015m3 - 2019m12                                       Lags =       2
-------------------------------------------------------------------------------
                                                              5%
maximum                                          trace    critical
  rank    parms       LL       eigenvalue   statistic     value
    0       6     166.65863            .      28.1258     25.32
    1      10     177.60004      0.31428       6.2430*    12.25
    2      12     180.72154      0.10205
-------------------------------------------------------------------------------
                                                              5%
maximum                                            max    critical
  rank    parms       LL       eigenvalue   statistic     value
    0       6     166.65863            .      21.8828     18.96
    1      10     177.60004      0.31428       6.2430     12.52
    2      12     180.72154      0.10205
-------------------------------------------------------------------------------
maximum
  rank    parms       LL       eigenvalue     SBIC        HQIC        AIC
    0       6     166.65863                 -5.326803  -5.456927  -5.539953
    1      10     177.60004      0.31428    -5.424063* -5.640935* -5.779312
    2      12     180.72154      0.10205    -5.391686  -5.651932  -5.817984
-------------------------------------------------------------------------------

3 . vecrank lpreparedfrozen lSpainExport, trend(rtrend) lags(2) ic max

                       Johansen tests for cointegration
Trend: rtrend                                          Number of obs =      58
Sample:  2015m3 - 2019m12                                       Lags =       2
-------------------------------------------------------------------------------
                                                              5%
maximum                                          trace    critical
  rank    parms       LL       eigenvalue   statistic     value
    0       6      74.09663            .      18.8680*    25.32
    1      10     80.008809      0.18443       7.0436     12.25
    2      12     83.530633      0.11436
-------------------------------------------------------------------------------
                                                              5%
maximum                                            max    critical
  rank    parms       LL       eigenvalue   statistic     value
    0       6      74.09663            .      11.8244     18.96
    1      10     80.008809      0.18443       7.0436     12.52
    2      12     83.530633      0.11436
```

maximum rank	parms	LL	eigenvalue	SBIC	HQIC	AIC
0	6	74.09663		-2.13501*	-2.265134	-2.34816
1	10	80.008809	0.18443	-2.058848	-2.27572*	-2.414097
2	12	83.530633	0.11436	-2.040275	-2.300522	-2.466574

4 . vecrank lpreparedfresh lSpainExport, trend(rtrend) lags(2) ic max

Johansen tests for cointegration

Trend: rtrend Number of obs = **58**

Sample: **2015m3 - 2019m12** Lags = **2**

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	6	157.28824	.	27.5253	25.32
1	10	168.52493	0.32123	5.0519*_	12.25
2	12	171.0509	0.08342		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	6	157.28824	.	22.4734	18.96
1	10	168.52493	0.32123	5.0519	12.52
2	12	171.0509	0.08342		

maximum rank	parms	LL	eigenvalue	SBIC	HQIC	AIC
0	6	157.28824		-5.003687	-5.13381	-5.216836
1	10	168.52493	0.32123	-5.111128*	-5.328*	-5.466377
2	12	171.0509	0.08342	-5.058215	-5.318462	-5.484514

5 . vecrank lnaturalfrozen lSpainExport, trend(rtrend) lags(2) ic max

Johansen tests for cointegration

Trend: rtrend Number of obs = **58**

Sample: **2015m3 - 2019m12** Lags = **2**

maximum rank	parms	LL	eigenvalue	trace statistic	5% critical value
0	6	153.88384	.	21.2076*_	25.32
1	10	161.15841	0.22186	6.6584	12.25
2	12	164.48763	0.10846		

maximum rank	parms	LL	eigenvalue	max statistic	5% critical value
0	6	153.88384	.	14.5491	18.96
1	10	161.15841	0.22186	6.6584	12.52
2	12	164.48763	0.10846		

maximum rank	parms	LL	eigenvalue	SBIC	HQIC	AIC
0	6	153.88384		-4.886294*	-5.016417	-5.099443
1	10	161.15841	0.22186	-4.85711	-5.073982*	-5.212359
2	12	164.48763	0.10846	-4.831895	-5.092142	-5.258194

```
6 . vecrank lnaturalfreshpp lSpainExport, trend(rtrend) lags(3) ic max

                      Johansen tests for cointegration
Trend: rtrend                                       Number of obs =      57
Sample:  2015m4 - 2019m12                                    Lags =       3
-------------------------------------------------------------------------------
                                                         5%
maximum                                      trace    critical
  rank    parms       LL       eigenvalue  statistic    value
    0      10     140.42207         .       21.6589*    25.32
    1      14     148.67838     0.25151      5.1463     12.25
    2      16     151.25151     0.08633
-------------------------------------------------------------------------------
                                                         5%
maximum                                       max     critical
  rank    parms       LL       eigenvalue  statistic    value
    0      10     140.42207         .       16.5126     18.96
    1      14     148.67838     0.25151      5.1463     12.52
    2      16     151.25151     0.08633
-------------------------------------------------------------------------------
maximum
  rank    parms       LL       eigenvalue     SBIC        HQIC        AIC
    0      10     140.42207                -4.217783   -4.436915   -4.576213
    1      14     148.67838     0.25151    -4.223755*  -4.53054*   -4.725557
    2      16     151.25151     0.08633    -4.172179   -4.52279    -4.745667
-------------------------------------------------------------------------------

7 . vecrank lnaturalfreshnpp lSpainExport, trend(rtrend) lags(3) ic max

                      Johansen tests for cointegration
Trend: rtrend                                       Number of obs =      57
Sample:  2015m4 - 2019m12                                    Lags =       3
-------------------------------------------------------------------------------
                                                         5%
maximum                                      trace    critical
  rank    parms       LL       eigenvalue  statistic    value
    0      10     201.58947         .       19.5316*    25.32
    1      14     207.75806     0.19462      7.1944     12.25
    2      16     211.35529     0.11858
-------------------------------------------------------------------------------
                                                         5%
maximum                                       max     critical
  rank    parms       LL       eigenvalue  statistic    value
    0      10     201.58947         .       12.3372     18.96
    1      14     207.75806     0.19462      7.1944     12.52
    2      16     211.35529     0.11858
-------------------------------------------------------------------------------
maximum
  rank    parms       LL       eigenvalue     SBIC        HQIC        AIC
    0      10     201.58947                -6.364008*  -6.583139   -6.722438
    1      14     207.75806     0.19462    -6.296726   -6.603511*  -6.798529
    2      16     211.35529     0.11858    -6.281083   -6.631694   -6.854571
-------------------------------------------------------------------------------

8 .
```

```
  ___  ____  ____  ____  ____(R)
 /__    /   ____/   /   ____/
___/   /   /___/   /   /___/
  Statistics/Data Analysis

    User: 1
```

```
1 . constraint 1 _b[lsmokedfreshpp] = 1

2 .
3 . constraint 2 _b[lSpainExport] = -1

4 .
5 . vec lsmokedfreshpp lSpainExport, trend(rtrend) rank(1) lags(2) bconstraint(1/2)

  Iteration 1:     log likelihood = 93.886565
  Iteration 2:     log likelihood = 94.308621
  Iteration 3:     log likelihood = 94.308724
  Iteration 4:     log likelihood = 94.308725
  Iteration 5:     log likelihood = 94.308725
  Iteration 6:     log likelihood = 94.308725
  Iteration 7:     log likelihood = 94.308725

  Vector error-correction model

  Sample:  2017m7 - 2019m12                   Number of obs     =         30
                                              AIC               =  -5.687248
  Log likelihood =  94.30872                  HQIC              =  -5.552772
  Det(Sigma_ml)  =  6.38e-06                  SBIC              =  -5.266889
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lsmokedfreshpp	4	.041093	0.0458	1.247277	0.8703
D_lSpainExport	4	.072743	0.3334	13.00492	0.0113

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lsmokedfreshpp						
_ce1 L1.	-.0719698	.0912022	-0.79	0.430	-.2507229	.1067833
lsmokedfreshpp LD.	.0017561	.0447182	0.04	0.969	-.0858899	.0894021
lSpainExport LD.	-.0911702	.0998407	-0.91	0.361	-.2868544	.1045141
_cons	.0006062	.007693	0.08	0.937	-.0144719	.0156842
D_lSpainExport						
_ce1 L1.	.5393729	.1614458	3.34	0.001	.222945	.8558008
lsmokedfreshpp LD.	.0251903	.0791599	0.32	0.750	-.1299602	.1803408
lSpainExport LD.	.3549359	.1767376	2.01	0.045	.0085366	.7013352
_cons	.0000809	.0136181	0.01	0.995	-.0266102	.026772

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	0	.	.

Identification: beta is overidentified

```
 ( 1)  [_ce1]lsmokedfreshpp = 1
 ( 2)  [_ce1]lSpainExport = -1

------------------------------------------------------------------------------
        beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
_ce1         |
lsmokedfreshpp |        1          .        .       .            .           .
 lSpainExport |       -1          .        .       .            .           .
       _trend |  -.0011583   .0027179    -0.43   0.670    -.0064854    .0041687
        _cons |  -1.77114          .        .       .            .           .
------------------------------------------------------------------------------
LR test of identifying restrictions: chi2(1) = 5.359      Prob > chi2 = 0.021

 6 . test ([D_lsmokedfreshpp]: L._ce1)

 ( 1)  [D_lsmokedfreshpp]L._ce1 = 0

           chi2(  1) =    0.62
         Prob > chi2 =    0.4300

 7 . test ([D_lSpainExport]: L._ce1)

 ( 1)  [D_lSpainExport]L._ce1 = 0

           chi2(  1) =   11.16
         Prob > chi2 =    0.0008

 8 . constraint 1 _b[lsmokedfreshnpp] = 1

 9 .
10 . constraint 2 _b[lSpainExport] = -1

11 .
12 . vec lsmokedfreshnpp lSpainExport, trend(rtrend) rank(1) lags(2) bconstraint(1/2)

Iteration 1:     log likelihood = 172.39917
Iteration 2:     log likelihood = 172.40621
Iteration 3:     log likelihood = 172.40621
Iteration 4:     log likelihood = 172.40621
Iteration 5:     log likelihood = 172.40621

Vector error-correction model

Sample:  2015m3 - 2019m12                        Number of obs     =         58
                                                 AIC               =  -5.634697
Log likelihood =  172.4062                       HQIC              =  -5.510158
Det(Sigma_ml)  =  8.98e-06                       SBIC              =  -5.314973

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
D_lsmokedfresh~p      4     .045063   0.1229   7.563895   0.1089
D_lSpainExport        4     .072172   0.1908   12.73621   0.0126
----------------------------------------------------------------

------------------------------------------------------------------------------
                  |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+----------------------------------------------------------------
D_lsmokedfreshnpp |
             _ce1 |
              L1. |  -.0621116   .0492002    -1.26   0.207    -.1585423     .034319
                  |
  lsmokedfreshnpp |
              LD. |  -.2786882   .1288505    -2.16   0.031    -.5312305   -.0261459
                  |
     lSpainExport |
              LD. |  -.0448988   .0824414    -0.54   0.586     -.206481    .1166835
                  |
            _cons |   .0046211   .0060635     0.76   0.446    -.0072632    .0165053
------------------+----------------------------------------------------------------
D_lSpainExport    |
             _ce1 |
              L1. |   .2351859   .0787989     2.98   0.003      .080743    .3896289
                  |
  lsmokedfreshnpp |
```

LD.	**.0305197**	**.2063665**	**0.15**	**0.882**	**-.3739512**	**.4349906**
lSpainExport						
LD.	**.3201457**	**.1320379**	**2.42**	**0.015**	**.0613561**	**.5789353**
_cons	**.0012204**	**.0097113**	**0.13**	**0.900**	**-.0178134**	**.0202542**

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	**0**	.	.

Identification: beta is overidentified

(1) **[_ce1]lsmokedfreshnpp = 1**
(2) **[_ce1]lSpainExport = -1**

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lsmokedfreshnpp	**1**	.	.	.	.	.
lSpainExport	**-1**	.	.	.	.	.
_trend	**.0020707**	**.0020955**	**0.99**	**0.323**	**-.0020364**	**.0061777**
_cons	**-1.586629**	.	.	.	.	.

LR test of identifying restrictions: chi2(**1**) = **10.39** Prob > chi2 = **0.001**

```
13 . test ([D_lsmokedfreshnpp]: L._ce1)

 ( 1)  [D_lsmokedfreshnpp]L._ce1 = 0

           chi2(  1) =    1.59
         Prob > chi2 =    0.2068

14 . test ([D_lSpainExport]: L._ce1)

 ( 1)  [D_lSpainExport]L._ce1 = 0

           chi2(  1) =    8.91
         Prob > chi2 =    0.0028

15 . constraint 1 _b[lpreparedfrozen] = 1

16 .
17 . constraint 2 _b[lSpainExport] = -1

18 .
19 . vec lpreparedfrozen lSpainExport, trend(rtrend) rank(1) lags(2) bconstraint(1/2)

Iteration 1:     log likelihood = 79.903051
Iteration 2:     log likelihood = 79.906533
Iteration 3:     log likelihood = 79.906538
Iteration 4:     log likelihood = 79.906538
Iteration 5:     log likelihood = 79.906538
```

Vector error-correction model

```
Sample:  2015m3 - 2019m12                       Number of obs     =         58
                                                AIC               =  -2.445053
Log likelihood =  79.90654                      HQIC              =  -2.320514
Det(Sigma_ml)  =   .000218                      SBIC              =  -2.125329
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lpreparedfro~n	**4**	**.211902**	**0.3853**	**33.84147**	**0.0000**
D_lSpainExport	**4**	**.075081**	**0.1243**	**7.665943**	**0.1046**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lpreparedfrozen						
_ce1 L1.	**-.4657326**	**.1522315**	**-3.06**	**0.002**	**-.7641009**	**-.1673643**
lpreparedfrozen LD.	**-.2814801**	**.1319173**	**-2.13**	**0.033**	**-.5400333**	**-.0229269**
lSpainExport LD.	**.3827856**	**.3871158**	**0.99**	**0.323**	**-.3759473**	**1.141519**
_cons	**.0010501**	**.0279189**	**0.04**	**0.970**	**-.05367**	**.0557701**
D_lSpainExport						
_ce1 L1.	**.0736279**	**.0539383**	**1.37**	**0.172**	**-.0320891**	**.179345**
lpreparedfrozen LD.	**-.0987333**	**.0467406**	**-2.11**	**0.035**	**-.1903432**	**-.0071234**
lSpainExport LD.	**.2810534**	**.1371618**	**2.05**	**0.040**	**.0122212**	**.5498856**
_cons	**.0066422**	**.0098922**	**0.67**	**0.502**	**-.0127461**	**.0260304**

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	**0**	.	.

Identification: beta is overidentified

(1) **[_ce1]lpreparedfrozen = 1**
(2) **[_ce1]lSpainExport = -1**

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lpreparedfrozen	**1**	.	.	.	.	.
lSpainExport	**-1**	.	.	.	.	.
_trend	**.0033039**	**.0031712**	**1.04**	**0.297**	**-.0029115**	**.0095193**
_cons	**-1.159859**	.	.	.	.	.

LR test of identifying restrictions: chi2(**1**) = **.2045**   Prob > chi2 = **0.651**

20 . test ([D_lpreparedfrozen]: L._ce1)

(1) **[D_lpreparedfrozen]L._ce1 = 0**

chi2(1) = **9.36**
Prob > chi2 = **0.0022**

21 . test ([D_lSpainExport]: L._ce1)

(1) **[D_lSpainExport]L._ce1 = 0**

chi2(1) = **1.86**
Prob > chi2 = **0.1722**

```
22 . constraint 1 _b[lpreparedfresh] = 1

23 .
24 . constraint 2 _b[lSpainExport] = -1

25 .
26 . vec lpreparedfresh lSpainExport, trend(rtrend) rank(1) lags(2) bconstraint(1/2)
```

Iteration 1: log likelihood = **167.88471**
Iteration 2: log likelihood = **167.8889**
Iteration 3: log likelihood = **167.8889**
Iteration 4: log likelihood = **167.8889**

Vector error-correction model

Sample:	**2015m3 - 2019m12**	Number of obs =	**58**
		AIC =	**-5.478928**
Log likelihood =	**167.8889**	HQIC =	**-5.354389**
Det(Sigma_ml) =	**.0000105**	SBIC =	**-5.159204**

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lpreparedfresh	**4**	**.048289**	**0.2414**	**17.18636**	**0.0018**
D_lSpainExport	**4**	**.07207**	**0.1931**	**12.9258**	**0.0116**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lpreparedfresh						
_ce1 L1.	**-.1971163**	**.0490216**	**-4.02**	**0.000**	**-.2931969**	**-.1010356**
lpreparedfresh LD.	**-.073127**	**.1218072**	**-0.60**	**0.548**	**-.3118647**	**.1656107**
lSpainExport LD.	**-.1972141**	**.0926653**	**-2.13**	**0.033**	**-.3788347**	**-.0155934**
_cons	**.0057461**	**.0063953**	**0.90**	**0.369**	**-.0067885**	**.0182806**
D_lSpainExport						
_ce1 L1.	**.2105197**	**.0731636**	**2.88**	**0.004**	**.0671217**	**.3539176**
lpreparedfresh LD.	**.214447**	**.1817942**	**1.18**	**0.238**	**-.1418632**	**.5707572**
lSpainExport LD.	**.3819037**	**.1383007**	**2.76**	**0.006**	**.1108393**	**.6529681**
_cons	**.0053802**	**.0095448**	**0.56**	**0.573**	**-.0133273**	**.0240877**

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	**0**	.	.

Identification: beta is overidentified

```
 ( 1)  [_ce1]lpreparedfresh = 1
 ( 2)  [_ce1]lSpainExport = -1
------------------------------------------------------------------------------------
          beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+--------------------------------------------------------------------
_ce1           |
lpreparedfresh |          1          .        .       .            .           .
  lSpainExport |         -1          .        .       .            .           .
        _trend |  -.0028232   .0015904    -1.78   0.076    -.0059402    .0002939
         _cons |  -1.688777          .        .       .            .           .
------------------------------------------------------------------------------------
LR test of identifying restrictions: chi2(1) = 1.272        Prob > chi2 = 0.259

27 . test ([D_lpreparedfresh]: L._ce1)

 ( 1)  [D_lpreparedfresh]L._ce1 = 0

           chi2(  1) =   16.17
         Prob > chi2 =    0.0001

28 . test ([D_lSpainExport]: L._ce1)

 ( 1)  [D_lSpainExport]L._ce1 = 0

           chi2(  1) =    8.28
         Prob > chi2 =    0.0040

29 . constraint 1 _b[lnaturalfrozen] = 1

30 .
31 . constraint 2 _b[lSpainExport] = -1

32 .
33 . vec lnaturalfrozen lSpainExport, trend(rtrend) rank(1) lags(2) bconstraint(1/2)

Iteration 1:     log likelihood = 158.52984
Iteration 2:     log likelihood = 158.54919
Iteration 3:     log likelihood = 158.54919
Iteration 4:     log likelihood = 158.54919

Vector error-correction model

Sample:  2015m3 - 2019m12                       Number of obs     =         58
                                                AIC               =  -5.156869
Log likelihood =  158.5492                      HQIC              =   -5.03233
Det(Sigma_ml)  =  .0000145                      SBIC              =  -4.837145

Equation           Parms      RMSE     R-sq      chi2     P>chi2
------------------------------------------------------------------
D_lnaturalfrozen      4     .056645   0.2717   20.14884   0.0005
D_lSpainExport        4     .072352   0.1868   12.40463   0.0146
------------------------------------------------------------------

---------------------------------------------------------------------------------------
                 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+---------------------------------------------------------------------
D_lnaturalfrozen |
            _ce1 |
             L1. |  -.0394296   .0510951    -0.77   0.440    -.1395741    .0607149
                 |
  lnaturalfrozen |
             LD. |  -.4622585   .1225036    -3.77   0.000    -.7023612   -.2221557
                 |
    lSpainExport |
             LD. |  -.1976852   .1014452    -1.95   0.051    -.3965142    .0011439
                 |
           _cons |   .0097755   .0075909     1.29   0.198    -.0051024    .0246533
-----------------+---------------------------------------------------------------------
D_lSpainExport   |
            _ce1 |
             L1. |   .1895614   .0652628     2.90   0.004     .0616486    .3174742
                 |
  lnaturalfrozen |
             LD. |  -.0078317   .1564718    -0.05   0.960    -.3145107    .2988474
```

```
    lSpainExport |
             LD. |   .2908743   .1295743     2.24   0.025     .0369134    .5448352
                 |
           _cons |   .0020333   .0096957     0.21   0.834    -.0169699    .0210366
------------------------------------------------------------------------------------

Cointegrating equations

Equation           Parms    chi2     P>chi2
-------------------------------------------
_ce1                 0         .         .
-------------------------------------------

Identification:  beta is overidentified

 ( 1)  [_ce1]lnaturalfrozen = 1
 ( 2)  [_ce1]lSpainExport = -1
-------------------------------------------------------------------------------
         beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
--------------+----------------------------------------------------------------
_ce1          |
lnaturalfrozen|          1          .        .       .            .           .
  lSpainExport|         -1          .        .       .            .           .
        _trend|   .0008573   .0028445     0.30   0.763    -.0047177    .0064324
         _cons|  -1.160868          .        .       .            .           .
-------------------------------------------------------------------------------
LR test of identifying restrictions: chi2(1) = 5.218       Prob > chi2 = 0.022

34 . test ([D_lnaturalfrozen]: L._ce1)

 ( 1)  [D_lnaturalfrozen]L._ce1 = 0

           chi2(  1) =    0.60
         Prob > chi2 =    0.4403

35 . test ([D_lSpainExport]: L._ce1)

 ( 1)  [D_lSpainExport]L._ce1 = 0

           chi2(  1) =    8.44
         Prob > chi2 =    0.0037

36 . constraint 1 _b[lnaturalfreshpp] = 1

37 .
38 . constraint 2 _b[lSpainExport] = -1

39 .
40 . vec lnaturalfreshpp lSpainExport, trend(rtrend) rank(1) lags(3) bconstraint(1/2)

Iteration 1:     log likelihood = 143.93079
Iteration 2:     log likelihood = 144.08577
Iteration 3:     log likelihood = 144.08582
Iteration 4:     log likelihood = 144.08582
Iteration 5:     log likelihood = 144.08582
Iteration 6:     log likelihood = 144.08582

Vector error-correction model

Sample:  2015m4 - 2019m12                        Number of obs     =         57
                                                 AIC               =  -4.599502
Log likelihood =  144.0858                       HQIC              =  -4.418415
Det(Sigma_ml)  =  .0000218                       SBIC              =  -4.133543

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
D_lnaturalfres~p     6     .074786   0.2823   20.06196   0.0027
D_lSpainExport       6     .070547   0.2694   18.80274   0.0045
----------------------------------------------------------------
```

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lnaturalfreshpp						
_ce1						
L1.	-.1114451	.0731884	-1.52	0.128	-.2548918	.0320016
lnaturalfreshpp						
LD.	-.3527221	.1308887	-2.69	0.007	-.6092591	-.096185
L2D.	-.314438	.1270165	-2.48	0.013	-.5633858	-.0654902
lSpainExport						
LD.	-.0540432	.1404357	-0.38	0.700	-.3292921	.2212057
L2D.	.1835198	.1471918	1.25	0.212	-.1049707	.4720104
_cons	.0101356	.010131	1.00	0.317	-.0097208	.0299921
D_lSpainExport						
_ce1						
L1.	.1625469	.0690403	2.35	0.019	.0272303	.2978635
lnaturalfreshpp						
LD.	-.3046832	.1234703	-2.47	0.014	-.5466805	-.0626859
L2D.	-.2987802	.1198176	-2.49	0.013	-.5336184	-.0639419
lSpainExport						
LD.	.2498443	.1324762	1.89	0.059	-.0098044	.509493
L2D.	-.07853	.1388494	-0.57	0.572	-.3506698	.1936097
_cons	.0069492	.0095568	0.73	0.467	-.0117819	.0256802

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	0	.	.

Identification: beta is overidentified

(1) **[_ce1]lnaturalfreshpp = 1**
(2) **[_ce1]lSpainExport = -1**

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lnaturalfreshpp	1	.	.	.	.	.
lSpainExport	-1	.	.	.	.	.
_trend	-.0007244	.0031534	-0.23	0.818	-.0069049	.0054561
_cons	-.9733592	.	.	.	.	.

LR test of identifying restrictions: chi2(**1**) = **9.185** Prob > chi2 = **0.002**

41 . test ([D_lnaturalfreshpp]: L._ce1)

(1) **[D_lnaturalfreshpp]L._ce1 = 0**

chi2(1) = **2.32**
Prob > chi2 = **0.1278**

42 . test ([D_lSpainExport]: L._ce1)

(1) **[D_lSpainExport]L._ce1 = 0**

chi2(1) = **5.54**
Prob > chi2 = **0.0186**

```
43 . constraint 1 _b[lnaturalfreshnpp] = 1

44 .
45 . constraint 2 _b[lSpainExport] = -1

46 .
47 . vec lnaturalfreshnpp lSpainExport, trend(rtrend) rank(1) lags(3) bconstraint(1/2)

Iteration 1:     log likelihood = 206.4812
Iteration 2:     log likelihood = 206.5109
Iteration 3:     log likelihood = 206.51151
Iteration 4:     log likelihood = 206.51153
Iteration 5:     log likelihood = 206.51153
Iteration 6:     log likelihood = 206.51153
Iteration 7:     log likelihood = 206.51153
Iteration 8:     log likelihood = 206.51153
Iteration 9:     log likelihood = 206.51153
```

Vector error-correction model

Sample:	2015m4 - 2019m12	Number of obs	=	57
		AIC	=	-6.789878
Log likelihood =	206.5115	HQIC	=	-6.608791
Det(Sigma_ml) =	2.44e-06	SBIC	=	-6.323919

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lnaturalfres~p	6	.028732	0.4870	48.41825	0.0000
D_lSpainExport	6	.071766	0.2439	16.45222	0.0115

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lnaturalfreshnpp						
_ce1 L1.	-.081982	.0732149	-1.12	0.263	-.2254805	.0615166
lnaturalfreshnpp LD.	-.0358148	.1539143	-0.23	0.816	-.3374812	.2658517
L2D.	-.1075521	.1188585	-0.90	0.366	-.3405105	.1254064
lSpainExport LD.	.3089743	.0707703	4.37	0.000	.170267	.4476815
L2D.	-.0044182	.0802355	-0.06	0.956	-.1616769	.1528404
_cons	.0015948	.004247	0.38	0.707	-.0067292	.0099188
D_lSpainExport						
_ce1 L1.	.3393483	.1828706	1.86	0.063	-.0190714	.697768
lnaturalfreshnpp LD.	.7999498	.3844353	2.08	0.037	.0464704	1.553429
L2D.	-.0593767	.2968757	-0.20	0.841	-.6412424	.5224891
lSpainExport LD.	.3016945	.1767647	1.71	0.088	-.0447579	.6481469
L2D.	-.3441213	.2004061	-1.72	0.086	-.73691	.0486674
_cons	.0003853	.0106079	0.04	0.971	-.0204058	.0211764

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	0	.	.

Identification: beta is overidentified

```
 ( 1)  [_ce1]lnaturalfreshnpp = 1
 ( 2)  [_ce1]lSpainExport = -1
```

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lnaturalfreshnpp	1	.	.	.	.	.
lSpainExport	-1	.	.	.	.	.
_trend	.0037385	.0010533	3.55	0.000	.0016741	.0058028
_cons	-.8290415	.	.	.	.	.

```
LR test of identifying restrictions: chi2(1) = 2.493      Prob > chi2 = 0.114

48 . test ([D_lnaturalfreshnpp]: L._ce1)

 ( 1)  [D_lnaturalfreshnpp]L._ce1 = 0

           chi2(  1) =    1.25
         Prob > chi2 =    0.2628

49 . test ([D_lSpainExport]: L._ce1)

 ( 1)  [D_lSpainExport]L._ce1 = 0

           chi2(  1) =    3.44
         Prob > chi2 =    0.0635

50 .
```

```
                                                    ___  ____  ____  ____  ____(R)
                                                   /__    /   ____/   /   ____/
                                                  ___/   /   /___/   /   /___/
                                                    Statistics/Data Analysis

                                                      User: 1

1 . vec lsmokedfreshpp lSpainExport, trend(rtrend) rank(1) lags(2)

  Vector error-correction model

  Sample:  2017m7 - 2019m12                        Number of obs     =        30
                                                   AIC               =  -5.799203
  Log likelihood =  96.98804                       HQIC              =  -5.649784
  Det(Sigma_ml)  =  5.33e-06                       SBIC              =  -5.332137

  Equation           Parms      RMSE     R-sq      chi2     P>chi2
  ----------------------------------------------------------------
  D_lsmokedfreshpp     4     .031756   0.4302   18.87205   0.0008
  D_lSpainExport       4     .086337   0.0610   1.623672   0.8045
  ----------------------------------------------------------------

  ------------------------------------------------------------------------------
                   |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
  -----------------+------------------------------------------------------------
  D_lsmokedfreshpp |
              _ce1 |
               L1. |  -.9284357    .219651    -4.23   0.000    -1.358944   -.4979277
                   |
    lsmokedfreshpp |
               LD. |   .0081569   .0330793     0.25   0.805    -.0566774    .0729912
                   |
      lSpainExport |
               LD. |  -.0484342    .074972    -0.65   0.518    -.1953767    .0985082
                   |
             _cons |   .0010196   .0060537     0.17   0.866    -.0108454    .0128846
  -----------------+------------------------------------------------------------
  D_lSpainExport   |
              _ce1 |
               L1. |   .3610145   .5971898     0.60   0.545    -.8094561    1.531485
                   |
    lsmokedfreshpp |
               LD. |  -.0643293   .0899364    -0.72   0.474    -.2406015    .1119429
                   |
      lSpainExport |
               LD. |   .1656308   .2038349     0.81   0.416    -.2338781    .5651398
                   |
             _cons |   .0026221   .0164588     0.16   0.873    -.0296366    .0348808
  ------------------------------------------------------------------------------

  Cointegrating equations

  Equation           Parms    chi2     P>chi2
  -------------------------------------------
  _ce1                 1   1.974964   0.1599
  -------------------------------------------

  Identification:  beta is exactly identified

                   Johansen normalization restriction imposed
  ------------------------------------------------------------------------------
              beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
  ---------------+--------------------------------------------------------------
  _ce1           |
  lsmokedfreshpp |          1          .        .       .            .           .
    lSpainExport |    -.10439   .0742813    -1.41   0.160    -.2499786    .0411986
          _trend |  -.0026067   .0007281    -3.58   0.000    -.0040337   -.0011797
           _cons |  -3.224232          .        .       .            .           .
  ------------------------------------------------------------------------------
```

```
2 .  vec lsmokedfreshnpp lSpainExport, trend(rtrend) rank(1) lags(2)

Vector error-correction model

Sample:  2015m3 - 2019m12                        Number of obs     =         58
                                                 AIC               =  -5.779312
Log likelihood =     177.6                       HQIC              =  -5.640935
Det(Sigma_ml)  =  7.51e-06                       SBIC              =  -5.424063

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
D_lsmokedfresh~p      4     .039952   0.3105   23.8694   0.0001
D_lSpainExport        4     .075521   0.1140   6.820615   0.1457
----------------------------------------------------------------

------------------------------------------------------------------------------------
                   |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
D_lsmokedfreshnpp  |
              _ce1 |
               L1. |  -.5969489   .1473388    -4.05   0.000    -.8857276   -.3081702
                   |
   lsmokedfreshnpp |
               LD. |  -.0152435   .1343858    -0.11   0.910    -.2786347    .2481478
                   |
      lSpainExport |
               LD. |  -.0999976    .073528    -1.36   0.174    -.2441099    .0441147
                   |
             _cons |   .0048268     .00533     0.91   0.365    -.0056197    .0152733
-------------------+----------------------------------------------------------------
D_lSpainExport     |
              _ce1 |
               L1. |   .5127254    .278509     1.84   0.066    -.0331422    1.058593
                   |
   lsmokedfreshnpp |
               LD. |  -.1200388   .2540244    -0.47   0.637    -.6179174    .3778398
                   |
      lSpainExport |
               LD. |   .2759241   .1389873     1.99   0.047      .003514    .5483342
                   |
             _cons |   .0056197    .010075     0.56   0.577     -.014127    .0253663
------------------------------------------------------------------------------------

Cointegrating equations

Equation           Parms    chi2     P>chi2
-------------------------------------------
_ce1                  1   27.56052   0.0000
-------------------------------------------

Identification:  beta is exactly identified

                 Johansen normalization restriction imposed
---------------------------------------------------------------------------------
          beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
---------------+-----------------------------------------------------------------
_ce1           |
lsmokedfreshnpp|          1          .        .       .            .           .
  lSpainExport |  -.2720597   .0518228    -5.25   0.000    -.3736304    -.170489
        _trend |  -.0016827   .0005215    -3.23   0.001    -.0027048   -.0006606
         _cons |  -2.659881          .        .       .            .           .
---------------------------------------------------------------------------------
```

```
3 . vec lpreparedfrozen lSpainExport, trend(rtrend) rank(1) lags(2)
```

Vector error-correction model

Sample:	2015m3 - 2019m12	Number of obs =	58
		AIC =	-2.414097
Log likelihood =	80.00881	HQIC =	-2.27572
Det(Sigma_ml) =	.0002172	SBIC =	-2.058848

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lpreparedfro~n	4	.214768	0.3685	30.92921	0.0000
D_lSpainExport	4	.074065	0.1479	9.195935	0.0564

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lpreparedfrozen						
_ce1 L1.	-.3992169	.145407	-2.75	0.006	-.6842093	-.1142245
lpreparedfrozen LD.	-.3167052	.1316493	-2.41	0.016	-.5747331	-.0586774
lSpainExport LD.	.3748863	.3996926	0.94	0.348	-.4084969	1.158269
_cons	.0014507	.0285726	0.05	0.960	-.0545505	.0574519
D_lSpainExport						
_ce1 L1.	.0916904	.0501448	1.83	0.067	-.0065916	.1899724
lpreparedfrozen LD.	-.1072548	.0454004	-2.36	0.018	-.1962378	-.0182717
lSpainExport LD.	.3062202	.1378374	2.22	0.026	.0360639	.5763764
_cons	.0063161	.0098535	0.64	0.522	-.0129964	.0256286

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	1	10.2361	0.0014

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lpreparedfrozen	1	.	.	.	.	.
lSpainExport	-1.286104	.4019842	-3.20	0.001	-2.073979	-.4982297
_trend	.0046183	.0040528	1.14	0.254	-.0033251	.0125617
_cons	-.7399326	.	.	.	.	.

4 . vec lpreparedfresh lSpainExport, trend(rtrend) rank(1) lags(2)

Vector error-correction model

Sample:	**2015m3 - 2019m12**	Number of obs =	**58**
		AIC =	**-5.466377**
Log likelihood =	**168.5249**	HQIC =	**-5.328**
Det(Sigma_ml) =	**.0000103**	SBIC =	**-5.111128**

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lpreparedfresh	**4**	**.046872**	**0.2853**	**21.15681**	**0.0003**
D_lSpainExport	**4**	**.073471**	**0.1615**	**10.20487**	**0.0371**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lpreparedfresh						
_ce1 L1.	**-.2832685**	**.0631886**	**-4.48**	**0.000**	**-.4071159**	**-.1594212**
lpreparedfresh LD.	**-.039331**	**.1193766**	**-0.33**	**0.742**	**-.2733049**	**.1946429**
lSpainExport LD.	**-.212561**	**.0909751**	**-2.34**	**0.019**	**-.3908688**	**-.0342531**
_cons	**.0051292**	**.0062629**	**0.82**	**0.413**	**-.0071459**	**.0174043**
D_lSpainExport						
_ce1 L1.	**.2388823**	**.0990477**	**2.41**	**0.016**	**.0447524**	**.4330122**
lpreparedfresh LD.	**.1828158**	**.1871221**	**0.98**	**0.329**	**-.1839368**	**.5495684**
lSpainExport LD.	**.3627107**	**.1426029**	**2.54**	**0.011**	**.0832142**	**.6422072**
_cons	**.0060822**	**.0098171**	**0.62**	**0.536**	**-.013159**	**.0253234**

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	**1**	**24.24172**	**0.0000**

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lpreparedfresh	**1**	.	.	.	.	.
lSpainExport	**-.6965068**	**.1414632**	**-4.92**	**0.000**	**-.9737697**	**-.4192439**
_trend	**-.0043239**	**.0014049**	**-3.08**	**0.002**	**-.0070774**	**-.0015704**
_cons	**-2.131514**	.	.	.	.	.

5 . vec lnaturalfrozen lSpainExport, trend(rtrend) rank(1) lags(2)

Vector error-correction model

Sample:	**2015m3 - 2019m12**	Number of obs =	**58**
		AIC =	**-5.212359**
Log likelihood =	**161.1584**	HQIC =	**-5.073982**
Det(Sigma_ml) =	**.0000132**	SBIC =	**-4.85711**

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lnaturalfrozen	**4**	**.0521**	**0.3839**	**33.02926**	**0.0000**
D_lSpainExport	**4**	**.075729**	**0.1091**	**6.492191**	**0.1653**

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lnaturalfrozen						
_ce1						
L1.	**-.5051555**	**.157073**	**-3.22**	**0.001**	**-.813013**	**-.197298**
lnaturalfrozen						
LD.	**-.2265052**	**.1363959**	**-1.66**	**0.097**	**-.4938364**	**.0408259**
lSpainExport						
LD.	**-.1734953**	**.0922247**	**-1.88**	**0.060**	**-.3542523**	**.0072617**
_cons	**.0065588**	**.0069833**	**0.94**	**0.348**	**-.0071282**	**.0202457**
D_lSpainExport						
_ce1						
L1.	**.3912887**	**.228312**	**1.71**	**0.087**	**-.0561946**	**.838772**
lnaturalfrozen						
LD.	**-.0896199**	**.198257**	**-0.45**	**0.651**	**-.4781964**	**.2989567**
lSpainExport						
LD.	**.2075638**	**.1340523**	**1.55**	**0.122**	**-.0551738**	**.4703014**
_cons	**.0084674**	**.0101504**	**0.83**	**0.404**	**-.0114271**	**.0283619**

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	**1**	**2.0904**	**0.1482**

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lnaturalfrozen	**1**	.	.	.	.	.
lSpainExport	**-.1163323**	**.080461**	**-1.45**	**0.148**	**-.2740329**	**.0413684**
_trend	**-.003431**	**.0008084**	**-4.24**	**0.000**	**-.0050155**	**-.0018465**
_cons	**-2.474421**	.	.	.	.	.

```
6 . vec lnaturalfreshpp lSpainExport, trend(rtrend) rank(1) lags(3)

Vector error-correction model

Sample:  2015m4 - 2019m12                      Number of obs     =         57
                                               AIC               =  -4.725557
Log likelihood =  148.6784                     HQIC              =   -4.53054
Det(Sigma_ml)  =  .0000186                     SBIC              =  -4.223755

Equation           Parms      RMSE     R-sq      chi2     P>chi2
----------------------------------------------------------------
D_lnaturalfres~p     6     .066223   0.4373   38.85034   0.0000
D_lSpainExport       6     .073594   0.2049   12.88516   0.0449
----------------------------------------------------------------

------------------------------------------------------------------------------------
                   |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------------+----------------------------------------------------------------
D_lnaturalfreshpp  |
              _ce1 |
               L1. |  -.9010719   .2207244    -4.08   0.000    -1.333684   -.4684601
                   |
   lnaturalfreshpp |
               LD. |   .1325274   .1736593     0.76   0.445    -.2078385    .4728933
              L2D. |  -.0213495   .1371772    -0.16   0.876     -.290212    .2475129
                   |
      lSpainExport |
               LD. |   -.132571   .1256948    -1.05   0.292    -.3789282    .1137862
              L2D. |    .079603   .1303588     0.61   0.541    -.1758956    .3351015
                   |
             _cons |   .0031107   .0090091     0.35   0.730    -.0145468    .0207681
-------------------+----------------------------------------------------------------
D_lSpainExport     |
              _ce1 |
               L1. |   .2377646   .2452923     0.97   0.332    -.2429994    .7185286
                   |
   lnaturalfreshpp |
               LD. |  -.3676527   .1929885    -1.91   0.057    -.7459033    .0105979
              L2D. |  -.3427601   .1524458    -2.25   0.025    -.6415485   -.0439717
                   |
      lSpainExport |
               LD. |   .2048081   .1396853     1.47   0.143    -.0689701    .4785863
              L2D. |  -.1521164   .1448685    -1.05   0.294    -.4360534    .1318206
                   |
             _cons |   .0117887   .0100118     1.18   0.239    -.0078341    .0314115
------------------------------------------------------------------------------------

Cointegrating equations

Equation           Parms    chi2     P>chi2
-------------------------------------------
_ce1                 1   1.602835   0.2055
-------------------------------------------

Identification:  beta is exactly identified

                 Johansen normalization restriction imposed
----------------------------------------------------------------------------------
            beta |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-----------------+----------------------------------------------------------------
_ce1             |
 lnaturalfreshpp |          1          .        .       .            .           .
    lSpainExport |  -.0941758   .0743866    -1.27   0.206    -.2399709    .0516193
          _trend |  -.0041577    .000735    -5.66   0.000    -.0055982   -.0027171
           _cons |  -2.348149          .        .       .            .           .
----------------------------------------------------------------------------------
```

```
7 . vec lnaturalfreshnpp lSpainExport, trend(rtrend) rank(1) lags(3)

Vector error-correction model

Sample:  2015m4 - 2019m12                      Number of obs     =         57
                                               AIC               =  -6.798529
Log likelihood =  207.7581                     HQIC              =  -6.603511
Det(Sigma_ml)  =  2.34e-06                     SBIC              =  -6.296726
```

Equation	Parms	RMSE	R-sq	chi2	P>chi2
D_lnaturalfres~p	6	.026949	0.5487	60.79627	0.0000
D_lSpainExport	6	.074121	0.1935	11.99397	0.0621

	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
D_lnaturalfreshnpp						
_ce1						
L1.	-.4581724	.1596694	-2.87	0.004	-.7711186	-.1452261
lnaturalfreshnpp						
LD.	.1600631	.1632244	0.98	0.327	-.1598509	.479977
L2D.	-.0784518	.1078195	-0.73	0.467	-.2897741	.1328706
lSpainExport						
LD.	.1251486	.0968651	1.29	0.196	-.0647036	.3150008
L2D.	-.1068769	.0853502	-1.25	0.210	-.2741604	.0604065
_cons	.0015981	.0036939	0.43	0.665	-.0056417	.008838
D_lSpainExport						
_ce1						
L1.	.0855446	.4391561	0.19	0.846	-.7751856	.9462747
lnaturalfreshnpp						
LD.	.8444154	.4489338	1.88	0.060	-.0354788	1.72431
L2D.	-.2170948	.2965478	-0.73	0.464	-.7983178	.3641282
lSpainExport						
LD.	.1498576	.2664188	0.56	0.574	-.3723136	.6720288
L2D.	-.4346287	.2347481	-1.85	0.064	-.8947265	.0254691
_cons	.0085596	.0101597	0.84	0.400	-.0113531	.0284722

Cointegrating equations

Equation	Parms	chi2	P>chi2
_ce1	1	172.2925	0.0000

Identification: beta is exactly identified

Johansen normalization restriction imposed

beta	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
_ce1						
lnaturalfreshnpp	1	.	.	.	.	.
lSpainExport	-.689749	.0525482	-13.13	0.000	-.7927416	-.5867564
_trend	.0015769	.0005195	3.04	0.002	.0005588	.0025951
_cons	-1.284254	.	.	.	.	.

8 .