Primary Results and Possible Improvements

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1. Preliminary data processing
   a. Data Set
   In this article, we are interested in the transmission between food and energy prices. Further, we are interested in the data generating mechanism of the whole price system. The data source is the monthly price of all US cities from January 1990 to August 2011. There are 123 price vectors in the data set while each price vector has 252 observations. After removing price vectors with too many missing pieces to data, we have a subsample with 23 price vectors. 4 of them are energy prices while the other 19 price vectors are food prices.
   b. Plot the data
   The data plot does not show obvious relation between food and energy prices except the following results:
   R1. First, all prices have a common trend of increasing. ***(Univariate Plot)(Bivariate Plot)***
   R2. Some prices such as fruit show strong seasonality. ***(Univariate Plot)***
   R3. Most prices have increasing volatilities.***(Univariate Plot)***
   R4. There is a common jump around year 2007 and year 2008.***(Univariate Plot)***
   c. Transformation of the data
   By R3, a log transformation is applied to the data. By such transformation, an increase in variable could be interpreted as the percentage change, and hence economically as the elasticity. I will use the term "data" as the log transformation of the original data thereafter.

2. The univariate characteristics of price vectors
   a. Stationarity
   Motivation: In order to check the underlying data generating mechanism (DGM), we tested stationarity of the data univariately first. If the DGM of a single price vector appear to be the same over time, then it could some statistical evidence of that the joint distribution of the whole 23 price vectors could be the same over time, i.e., the whole data is generated by a single DGM (or a single joint distribution). Later, we will further check univariate structural break (jumps) and structural breaks in cointegration, which will provide further information about the DGM.

   In the model, I used three tests to test the stationarity. They are Augmented Dickey-Fuller test (ADF test), Phillips-Perron test and Kwiatkowski–Phillips–Schmidt–Shin test. I used ADF test as the primary test, although in most situation all three tests agree.

The staionarity tests have the following results:

R5. All the price vectors are not stationary;***(Results by 2.25.2012/Table 4)***

R6. Most price vectors are integrated by order 1.***(Results by 2.25.2012/Table 4)***

R7. By R6, we think that the price vectors could be AR(1), so we tested stationarity of the first difference of the data. And the test shows all the prices are stationary after first differencing.***(Results by 12.19.2011/Table 1)***

R8. By R7, we think that the prices may have a linear trend in them. So I tested the linear trend. The test shows that all prices have a linear trend.I used parametric and nonparametric tests on testing whether there is a trend. Both agree that ***Peanut Butter*** may not have a trend.***(Results by 2.25.2012/Table 2)***

R9. By R4 that some prices have strong seasonality, I tested the tested stationarity of the first difference of the data. And the test shows all the prices are stationary after twelfth differencing.***(Results by 2.25.2012/Table 4)***

R10. By R7 and R9, the detrended and deseasonalized data should be stationary. I test stationarity tests on it and the tests agree with the statement.***(Results by 11.17.2011/Table "Random Components")***

b. Test the univariate structural breaks (jumps)

Motivated by exploring the DGM of the whole price system, I tested the structural breaks of the price vectors univariately. The test shows the following results:

R11. There is no consistency in break periods, except broad windows e.g. 2007-8. Note this result is consistent with our preliminary observation (R4).***(Results by 2.25.2012/Table 1)***

Possible Improvements:

I1. A stationary test with structural break could be done. Expected results:

ER1. Some price vectors that are not stationary over the full period could be shown as stationary within the structural break provided by R11.

3. The bivariate characteristics of price vectors

Motivation: By implementing the bivariate analysis of a pair of prices, we want to explore the relation between two prices, especially one food price and one energy price. Further, we can check the dynamic of the two prices, especially the transmission in level between food prices and energy prices.

a. Bivariate VAR of stationary data

By R7, R9 and R10, we now have three stationary data sets: 1st difference, 12th difference and detrended-deseasonalized data. So we constructed a bivariate VAR on 1st and 12th difference data sets and implement the Granger-causality test. These are the main results:

R12. The causality test on 1st difference VAR shows that there is significant relation between prices within meet section, dairy product section, fruit section and energy section. ***(Results by 2.25.2012/Table 8)***

R13. The causality test on 1st difference VAR shows that ***Electricity*** price has a significant effect on most food prices except for 9 kinds of food: ***Bread, Chuck Roast, Bologna, Fresh Chicken, Milk, Butter, Cheese and Potato***.***(Results by 2.25.2012/Table 8)***

R14. The causality test on 1st difference VAR shows that no other energy prices have significant effect on most food prices.***(Results by 2.25.2012/Table 8)***

R15. The 12th VAR results agree with R12.***(Results by 2.25.2012/Table 9)***

R16. The causality test on 12th difference VAR agrees with R14.***(Results by 2.25.2012/Table 9)***

R17. Price vectors with strong periodity shows more significant results when differenced using 12 lags. (Monthly data) However, no theoretical reason is founded.***(Results by 2.25.2012/Table 9)***

Possible Improvements:

I2. A VAR on detrended-deseasonalized data could be modeled and a Granger-Causality test could be done. Expected Results:

ER2. The detrended-deseasonalized data should be quite like a pure noise, so there should not be many summarizable results.

I3. A VAR with structural break could be estimated. Expected results:

ER3. There could be some structural breaks in the bivariate VAR and the Granger-Causality test should be more significant than that of R12-R16.

I4. An impulse response function (IRF) could be constructed based on the VARS. Expected results:

ER4. The dynamic could be clearer. However, the IRF could be hard to summarize.

b. Bivariate ECM of non-stationary data

By R5, all prices are not stationary and most are I(1). So we can construct a VECM so that we can check the stable relation between two price vectors. I used two methods for testing cointegration of 19 series with unit root:

(1). For a bivariate pair, regress one on the other, and test on the residuals. If the residuals are stationary, then we conclude the two seires are cointegrated; if not, then conclude they not integrated.

(2). For a bivariate pair, use Johansen procedure to test the rank of cointegration. If $r<=0$ is rejected, then we conclude they are cointegratedpairly.

After constructing a VECM, I analyzed the long-run (LR) and short-run (SR) effects. Here are the primary results:

R18. Respectively inside meat products, dairy products, fruits and energy prices there are evidence of cointegration. This agrees with R12 and R15.***(Results by 2.25.2012/Table 5)***

R19. Between three kinds of beef, between dairy products and between energy prices there is very strong evidence of cointegration.***(Results by 2.25.2012/Table 5)***

R20. Inside Energy prices, Dairy products and beef products have perfect LR impacts on each other. ***(Results by 2.25.2012/Table 7)***
R21. Energy prices and food prices have dual directional effects and causality. ***(Results by 2.25.2012/Table 7)***
Possible Improvements:
I5. The LR and SR effects could be better modeled. Expected results:
ER5. There could be more accurate results that agree with other results.

c. Bivariate ECM of some vectors with structural break

For that the process of testing for structural break is complicated, I chose only 4 food vectors and 1 energy vector to analyze VECM with structural break. The test procedure of structural break is as followed:

(1) Test structural break over the whole period using OLS-CUSUM,MOSUM,supF, expF tests.
(2)If rejected, find a structural break by BIC/RSS. And test the structural break on divided intervals.
(3)Repeat until the entire interval has no structural break.

And the result is:
R22.

Name	Beef	chicken	milk	apple	electricity
Beef	NA	67	No Breaks	No Breaks	191
Chicken	155	NA	110,163,204	92,183	No Breaks
Milk	No Breaks	No Breaks	NA	No Breaks	No Breaks
Apple	130	225	No Breaks	NA	No Breaks
Electricity	No Breaks	67	No Breaks	31 ,58	NA

(Results of 4 Food vs. 1 Energy (Structural Break))
Further, I construct cointegration tests within each structural breaks and results show:
R23. Only ***Electricity and Apple*** are cointegrated in the interval [31,7] and [59, 259]. This result does not agree with R13. ***(Results of 4 Food vs. 1 Energy (Cointegration in subsample))***
In addition, I convert VEC to VAR and analyzed the IRF bivariately with in each structural break. And
R24. The IRF from ***Electricity*** to the other 4 food prices does not show systematic results. ***(Results of 4 Food vs. 1 Energy (VAR Coefficients and IRF))***
R23 and R24 are quire frustrating. By R2, I doubted that the strong seasonality may be the reason of R23 and R24. So I implemented a test on detrended-deseasonalized data (here I expanded the 5 vectors to 7 vectors-add in two energy vectors). And results show:
R25. All the detrended-deseasonalized vectors are cointegrated with very high significant statistics. This result could highly be problematic for that: First, the detrended-deseasonalized data should be quite like pure noise and hence should not be cointegrated; second, the detrended-deseasonalized data is stationary based on R10. So I should

analyze it under the scheme of VAR rather than VECM. ***(Raw Results of DTDS 4 Food vs. 3 Energy/CI test of DSDT data)***

Based on the failure of R25, I implemented a cointegration test with allowance of trend and seasonal part as argument in coding rather than first detrend-deseasonaliz and then test cointegration. And this result shows very different results as that in R22:

<u>**R26.**</u> Energy prices are cointegrated. This agrees with R12, R15 and R18. ***(Raw Results of DTDS 4 Food vs. 3 Energy/CI test with trend and seasonal)***

<u>**R27.**</u>***Gasoline*** is cointegrated with most food prices. This does not agree with R13, R19 and R23. ***(Raw Results of DTDS 4 Food vs. 3 Energy/CI test with trend and seasonal)***

Possible Improvements:

<u>**I6.**</u> Construct cointegration test with structural breaks of other food and energy prices. Expected results:

<u>**ER6.**</u> The estimating process could be difficult computationally.

<u>**I7.**</u>Construct VAR and VECM using all vectors rather than bivariately. The expected results are:

<u>**ER7.**</u> We could be more clear about the system. But the estimating process could be difficult computationally.

d. More Food and Energy cointegration

In order to see how structural breaks can affect the cointegration results, I expand the subsample to 9 Food and 4 Energy prices.

<u>**R28.**</u> I ran a test of cointegration 9 Food and 4 Energy prices cointegration without structural break. In the results, several pairs with *Potato* and *Lettuce* have higher cointegration order of 1. This is problematic for any two vectors could not be cointegrated by order higher than 1. So I drop the *Potato* and *Lettuce*. A possible reason that the cointegration can not be applied to the two vectors (probably one more vector: *Gasoline*) is that they univariately are not I(1), referring the previous results of the ADF test <u>**R5**</u>. ***(Results of 7 Food vs. 4 Energy/Table Choosing the vectors)***

After dropping the two vectors (*Potato* and *Lettuce),* I ran cointegration test with structural breaks in comparison to cointegration without structural breaks.

<u>**R29.**</u> The cointegration table of 7 food prices and 4 energy prices

This table is a subsample of the table ***Results by 2.25.2012/Table 5. (Results by 2.25.2012/CI test (full period))***

<u>**R30.**</u> Then I indentify the structural break in the cointegration. This result has same fashion as R22.

	Bread	Beef	Chicken	Milk	Apple	Orange Juice	Potato Chip
FUEL OIL	No	No	No	86,221	195	No	48,89,135,175,221
ELECTR.	No	No	67	No	31 ,58	No/104,173	No/88
GAS	No	46	No	No	No/213	No	77(88),98,135,169,216
GASOLINE	No	No	No/64	110	No	No	88 ,130, 169, 216

Note that almost all bivariate VECM with *Potato Chip* have 4-5 structural breaks, which means the cointegrations may be nonlinear. And the common structural breaks here are probably because of the univariate structural breaks of *Potato Chip*. ***(Results by 2.25.2012/Structural Break)***

R31. The cointegration test with structural breaks
By allowing for structural breaks, we have more significant Cointegration results. For example, Gas➔Apple, Gasoline➔Chicken, All energy prices➔Potato Chip are not cointegrated without structural breaks, but they are cointegrated with structural breaks, although the cointegration is doubted to be nonlinear (for the Potato Chip case).
(Results by 2.25.2012/CI test (structural break))