Have Commodity Index Funds Increased Price Linkages between Commodities?

by

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To shed more light on the ongoing debate on the role of commodity index funds on recent commodity price spikes, we investigate the linkages between commodity futures prices surrounding the time period of increased index fund activity. We take a Bayesian approach to test stationarity and cointegration of commodity pairs and trios. We find that simple correlation coefficients between futures prices and the probability of non-stationarity of the series have increased over time as the size of index fund trading became larger. However, our cointegration test results show no evidence for an increase in cointegration.

Key words:cointegration, commodity futures, index funds

Introduction

Commodity index funds have been blamed by some for recent price spikes in many agricultural commodities (Gilbert 2010), for causing commodity price bubbles associated with those same price spikes (De Schutter 2010), and generally distorting the price discovery function of commodity futures markets. Various recent research papers have advanced conclusions in support of (Baffes and Haniotis 2010) and against (Stoll and Whaley 2010, Sanders and Irwin 2010, Wright 2011) these claims. What has not been investigated is whether the surge in the size of the commodity index funds has translated into an increase in the linkages among commodity prices.

Prices of some commodities are linked for biological reasons (e.g., corn gets fed to cattle) while other prices are linked due to substitutability in production (farmers can switch easily between growing two or more crops) or consumption (people will switch from wheat to corn for subsistence calories if it is cheaper). Other commodities have no particular reason for any price linkage between them and we would therefore expect to find their prices relatively uncorrelated. However, if commodity index funds do impact either the spot or futures prices of commodities (an open question), then the large increase in the size of commodity index funds over the past decade may have introduced stronger linkages across commodities and led previously unconnected prices to be correlated (or in the case of non-stationary series, possibly cointegrated).

The case for a large impact by commodity index funds on commodity prices and futures markets is based on the idea that a new class of investors has entered commodity futures markets (Gilbert 2010). These new investors, commodity index funds, generally take long only positions and also generally invest in a relatively fixed basket of commodity assets. The first of these two characteristics could push up commodity prices if the demand for long futures positions actually changes the equilibrium of supply and demand in commodity futures markets and spot prices remain linked to the futures.

The second could introduce a new reason for seemingly unrelated commodity prices to behave as if linked by some fundamental relationship since these new buyers take positions in some fixed proportions. More formally, we investigate the possibility that the growth of commodity index funds has led previously uncointegrated commodity futures markets to become cointegrated.

It is worth noting that the actions by these commodity index funds might not cause an increase in cointegration among commodity markets for several reasons. First, fixed proportion demand in a set of commodity markets does not necessarily lead to cointegration among those markets. If this new demand represents a small share of total volume in these markets and does not dominate other trends, cycles, and shifts in these markets then one should not expect cointegration to result. Second, while understanding cointegration as a shared trend is a useful construct, one should remember that cointegration implies an equilibrium relationship between the variables involved as best viewed through the error-correction represention of a time series model of a set of cointegrated series. Commodity index funds that simply take new funds and buy a basket of commodity futures contracts according to some pre-determined portfolio model would not represent actions based on an equilibrium ratio in futures prices nor would they drive deviations from such an equilibrium back into equilibrium. However, if commodity index funds had freedom to time purchases of individual commodities within their baskets so that they tended to buy the "cheaper" commodities in higher proportions, balancing their actions out over quarters or years, then such actions would represent a new force pushing possibily unrelated commodity prices into an equilibrium relationship. Under this scenario, the increase in volume from commodity index funds in commodity markets over the last decade could indeed result in an observed increase in cointegration among various commodity futures markets.

We test a wide array of commodity futures prices for a trend in linkages over time. In particular, we estimate the correlations between commodities and test for cointegration (given that non-stationarity is found in the individual commodity prices) for data beginning in 1990 and ending in 2003, 2008, and 2011. These three dates will represent the before, during, and after points in the increased size of the commodity index funds. Since farming, processing, and consumption practices have not experienced any major shifts over that particular, quite short, time period, it seems reasonable to ascribe any changes found in commodity market linkages over this time frame to the growing influence of commodity index funds. Commodities included are corn, soybeans, live cattle, feeder cattle, lean hogs, cotton, cocoa, and crude oil. Some of these should be related and some should not; we hope this broad set of commodities will help to find any increase in cointegration over time. We use a Bayesian procedure to test for unit roots and cointegration (Dorfman 1995). The Bayesian cointegration test applied here allows for pairwise tests as well as tests of larger groups of price series that are particularly well-suited to the situation investigated in this paper.

Testing for Linkages between Commodity Prices

To examine whether linkages have increased among commodity prices due to the increase in activity in these markets by commodity index funds, we take a two-pronged approach. First, we examine the futures prices of a set of diverse commodities by investigating changes in simple correlations over different sample periods. Second, we examine the time series properties of the same set of futures prices to see if the probabilities of both unit roots and cointegration have changed over the same set of sample periods.

Correlations

The "state of the art" method for testing for changes in market linkages is to test for cointegration between the pair (or set) of prices being examined. If prices are cointegrated, they are linked by some long-run equilibrium relationship that is causing them to move together in the sense that over time the prices cannot diverge too far from their long-run equilibrium ratio. However, if the futures prices to be examined are not non-stationary (that is, do not have unit roots), then they cannot be cointegrated and a cointegration test cannot determine if the markets have become more "linked over time."

Because futures prices may or may not be non-stationary in the difference-stationary sense, we also compute simple correlation coefficients between various pairs of futures price series for the periods of 1990-2003, 1990-2008, 1990-2011, and 2004-2011. If commodities that have no apparent reason to be linked exhibit a rising correlation as the importance of commodity index funds increase, we will take that as evidence that commodity index funds are having a significant effect in these commodity futures markets. Test of statistical significance can be performed on the correlation coefficients because asymptotically correlation coefficients have a variance equal to $1/T$ where T is the sample size.

A Bayesian Test for Non-Stationarity and Cointegration

To test the futures price series for non-stationarity and cointegration, we utilize a Bayesian procedure developed by Dorfman (1995). This approach is based on an autoregressive time series model of each futures price and utilizes both univariate and multivariate models. To begin, let the standard multivariate model under consideration be given by

$$y_t = \mu + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_p y_{t-p} + \epsilon_t, \tag{1}$$

where y_t is the set of m futures price series to be tested, μ is a vector of constants to be estimated that represent either the mean of the series if they are stationary or the trend if they are non-stationary, Φ_i is a set of autoregressive parameters to be estimated, and ϵ is assumed to be a zero-meaned Gaussian process with a constant covariance matrix Σ. The subscripts on the y_t denote time periods which are assumed to go from $t = 1, \cdots, T$ and the maximum lag included in the autoregressive process is p.

The long-run dynamic properties of such a time series can be analyzed easily through the matrix

$$A = \begin{bmatrix} \Phi_1 & I & 0 & \cdots & & & 0 \\ \Phi_2 & 0 & I & 0 & \cdots & & 0 \\ \Phi_3 & 0 & 0 & I & 0 & \cdots & 0 \\ \vdots & & & \ddots & & 0 & I \\ \Phi_p & \cdots & & \cdots & & 0 & 0 \end{bmatrix}, \tag{2}$$

where A is the transition matrix from the state space representation of the model in (1). The presence of non-stationary roots in the process in (1) translates to the matrix A having eigenvalues with magnitudes that are greater than one; unit roots would be eigenvalues with magnitude exactly equal to one; and stationary roots correspond to eigenvalues with magnitudes less than one. This suggests tests for non-stationarity can be centered on the eigenvalues of estimates of A while cointegration tests can be conducted by comparing the number of non-stationary roots in (1) to the number of non-stationary roots in the corresponding set of univariate autoregressive models for the set of variables in the vector y_t.

To implement such tests, we take a Bayesian approach. Given that in most applications we have little prior knowledge about likely autoregressive coefficients and that an informative prior is necessary in this model to ensure a well-behaved posterior distribution, we place an informative prior over the number of non-stationary roots in the process $\{y_t\}$. Denote the number of non-stationary roots in the process by λ and the discrete prior probabilities by

$$p(\lambda^M = k) = \omega_k, \quad k = 1, 2, \cdots, mp. \tag{3}$$

Priors in the above form can be placed on the multivariate series being tested and on each individual series of the set. If the number of non-stationary roots in each individual series is denoted by λ_j^U and the number of non-stationary roots in the full set of univariate models is λ^U, then the implied prior on the number of non-stationary roots in the set of m univariate models is given by

$$p(\lambda^U = k) = \omega_k^U = \sum_{\{k_j\} \in K_k} \left(\prod_{j=1}^{m} \omega_{k_j}^{j} \right), \quad k = 1, 2, \cdots, mp, \tag{4}$$

where K_k is a set which contains all the sets of m integers that sum to k so that (4) essentially finds all the combinations of the prior probabilities from the m univariate series that yield a total number of k non-stationary roots across the set of series.

Given these definitions, if we write the model in (1) in fairly standard matrix notation as $Y = X\Gamma + \epsilon$ and employ a standard Jeffreys prior on the error covariance matrix Σ, then the posterior distribution for the model is

$$p(\Gamma, \Sigma|Y, X) \propto p(\lambda(\Gamma))|\Sigma|^{-(T-p+m+1)/2} \exp\{-0.5\mathrm{tr}[S + (\Gamma - \hat{\Gamma})' X' X (\Gamma - \hat{\Gamma})]\}, \quad (5)$$

where S is the sum of squared errors and $\hat{\Gamma}$ is the usual OLS (or maximum likelihood) estimator.

The posterior distribution in (5) is not analytically tractable because of the discrete mass prior on the number of non-stationary roots which translates into a discontinuous step-function prior in the parameter space of the autoregressive coefficients in Γ (for details, see Dorfman 1995). Further, we are not interested in the posterior distribution of the structural parameters of (1), but rather in the posterior probabilities of various numbers of non-stationary roots. On both counts, numerical methods are the best approach to analyze this posterior distribution. Once a set of draws have been generated (details to be given shortly) from the posterior distribution in (5), the number of non-stationary roots for each draw can be easily computed through an eigenvalue decomposition of the A matrix given in (2). This allows for the straightforward construction of a numerical approximation to the posterior distribution of the number of non-stationary roots in $\{y_t\}$.

A test for non-stationarity is simply based on the posterior probability of $\lambda > 0$ and the test for cointegration centers on

$$\Psi = p(\lambda^M < \lambda^U) = \sum_{c=0}^{mp-1} p(\lambda^M = c)p(\lambda^U > c), \quad (6)$$

where Ψ is the posterior probability of cointegration and the formula above is implemented using the posterior probabilities computed from the numerical approximation to the posterior distribution of the number of non-stationary roots.

Data

We analyze eight different futures markets that can be categorized into four groups: grain (corn, soybeans), livestock (live cattle, feeder cattle, lean hogs), soft (cotton, cocoa), and energy (crude oil). Grain futures contracts are traded at the Chicago Board of Trade (CBOT), livestock futures at the Chicago Mercantile Exchange (CME), soft futures at the International Commodity Exchange (ICE), and energy futures at the New York Mercantile Exchange (NYMEX). Table 1 summarizes contract specifications for these selected futures markets.

For each commodity, we construct time series of end-of-month settlement prices from January 1990 through September 2011 by rolling over nearby contracts. As table 1 shows, contract expiration dates vary across commodities. To avoid delivery period problems, we roll over the first nearby contracts for all commodities but crude oil at the end of the month prior to contract expiration. For instance, for corn, in December, January, and February, March corn contract is used while in March and April, May corn, in May and June, July corn, in July and August, September corn, and in September through November, December corn contract is used. On the other hand, crude oil futures contracts expire on the third business day prior to the twenty-fifth calendar day of the month preceding the delivery month, which is the month prior to contract month. Accordingly, we roll over the crude oil nearby contract at the end of the month which is two months prior to contract month. Thus, in January we use March crude oil contract, in February we use April crude oil, in March we use May crude oil contract, etc.

In order to analyze the impact of index funds on commodity price linkages, we split our sample period into four sub-samples: 1990-2003, 1990-2008, 1990-2011, and 2004-2011. The number of observations for each sub-sample are 168, 228, 261, and 93. Table 2 presents summary statistics of futures prices for the entire sample period of 1990-2011.

In trying to construct sets of prices that had different probabilities of being tightly linked before commodity index funds and after, we settled on the following sets of pairs and trios: corn and cotton; corn and soybeans; corn and lean hogs; corn and live cattle; corn and crude oil; cocoa and crude oil; soybeans and lean hogs; live cattle and feeder cattle; corn, soybeans, and lean hogs; corn, live cattle, and feeder cattle; and corn, cocoa, and cotton. Some of these would be expected to be correlated or cointegrated, others seem to us completely unrelated by any market forces.

Econometric Results and Policy Implications

Numerical Methods for Bayesian Stationarity and Cointegration Tests

The advance of Bayesian statistical methods over the last twenty-five years has been built on the development of numerical methods for approximating posterior distributions that are not tractable analytically. The application in this paper falls into that category as the prior on the number of non-stationary roots leads to a posterior distribution that is not of a standard form. In addition to the prior distributions as specified above, we also add an additional truncation to the prior so that it has positive support only for the parameter space where all autoregressive parameters are less than 2 in absolute magnitude. This is to add assurance to the prior being informative enough to yield a proper posterior distribution. The prior on the number of non-stationary roots in each multivariate model is taken to be a Poisson with parameter equal to $0.9m$ where m is the number of commodities being modeled. The prior for each univariate series in a pair or trio is specified separately as a Poisson with parameter equal to 0.9 (since $m = 1$).

The generation of draws from our posterior distribution is accomplished using Gibbs sampling with a Metropolis-Hastings step. Gibbs sampling is an approach where random draws are generated for subsets of the full set of parameters to be estimated from the conditional distribution of each parameter subset (Casella and George 1992). The subsets are chosen in a manner designed to provide conditional distributions that are easy to generate random draws from. By sequentially drawing from these conditional distributions holding constant the other parameters at their most recently drawn random values, one can generate an empirical distribution of parameter sets that converges to the true, joint posterior distribution. A Metropolis-Hastings step is one in which draws are generated from a distribution different from the conditional posterior and then accepted with a random probability that is computed in such a manner as to adjust the frequency of the draws so as to match those that would have been generated from the actual conditional posterior distribution.

Our Gibbs sampler is simple. The covariance matrix Σ has a conditional posterior distribution that is an inverted-Wishart from which it is easy to generate draws. The conditional posterior of the autoregressive parameters is a truncated normal multiplied by the prior on the number of non-stationary roots. Because we cannot generate draws from this conditional distribution, we use an independence chain Metropolis-Hastings step here (Koop 2003). We generate draws from a scaled normal kernel of this conditional posterior as candidate draws (the scaling is to increase the covariance matrix of the multivariate normal in order to ensure sufficient draws from the tails of the true posterior). Because our candidate density only differs from the conditional posterior distribution by the prior distribution (which is what causes the problem in generating draws), the acceptance probability formula simplifies in this case to the ratio of the prior distribution value at the candidate draw to the prior distribution value at the previous accepted draw. That is, whenever a random variable generated from a uniform distribution on the interval [0,1] is less than the ratio of the prior at the new draw to the prior at the old draw, we accept the new draw and continue through the Gibbs sampler by generating a new covariance matrix. When the new, candidate draw is rejected, the previous draw for the autoregressive parameters is reused. We begin with the maximum likelihood estimator of the model, run the Gibbs sampler for 11,000 draws, discard the first 1,000 draws to remove dependence on the initial conditions, and approximate the posterior distribution with the remaining 10,000 draws. Convergence is confirmed by comparison of the means for the first and second half of the draws.

Stationarity Tests

To find cointegration we must have non-stationarity in the set of individual prices involved as a necessary condition. However, because we are interested in whether commodity futures prices are linked, all our analysis is in terms of pairs, or occasionally trios of series. Thus, when we test for stationarity, the results are presented for a set of commodities. Stationarity test results are given in table 3. Numbers shown are the posterior probability of no unit roots in that set of future price series for each sub-sample. That is, the table shows the probability that all prices in that set are stationary.

The results of the stationarity tests are very clear. In the earliest sub-sample, before commodity index funds are a factor, all our sets of future prices have quite high probabilities of stationarity in the range of 75 to 87 percent. As we move forward in time, these posterior probabilities generally drop (in almost all cases monotonically). For the last sub-sample, 2004-2011, the posterior probabilities of stationarity have decreased to the range of 14 to 69 percent. All the probabilities of stationarity for the last sub-sample are below the lowest one for the first sub-sample. A clear conclusion from these results is that something, perhaps commodity index fund-driven volume, has led commodity futures markets to be more non-stationary (more "efficient") in the past seven or eight years.

Correlation Results

Given the stationarity test results, we discuss the correlation results next, before the cointegration test results. Table 4 shows the correlation coefficients for our pairs of commodity futures prices. Because the variance of a correlation coefficient is simply $1/T$, any correlation coefficient in the sub-samples that are greater in absolute value than 0.15, 0.13, 0.12, or 0.20 respectively for our four sub-samples is significantly different from zero. The numbers in the table show that all but two pairs (cocoa-crude oil and cocoa-cotton) are significantly correlated in the earliest sub-sample. In the final sub-sample, 2004-2011, all the pairs are significantly correlated and the two pairs that were not are now highly correlated with estimated correlation coefficients of 0.63 and 0.64, respectively. All but one pair become more positively correlated over time and three pairs switch from negative correlation coefficients to strongly positive ones. When comparing the first and last sub-samples (1990-2003 and 2004-2011), a difference greater than 0.26 is a significant change in the correlation coefficient. We observe such significant changes in seven of the eleven pairs of future prices series.

These results certainly add to the empirical evidence in favor of an effect from the growth of commodity index funds. While correlation coefficients certainly do not prove causation, given the timing of the changes and the unlikeliness of an alternative explanation this evidence seems to provide at least some argument in favor of commodity index funds being behind these changes. After all, what production-based reason is there for cocoa and crude oil prices to be highly correlated? Why would no pairs of futures prices display a negative correlation?

Cointegration Test Results

Turning now to cointegration, table 5 contains the results of our Bayesian cointegration tests. Because of the low probability of non-stationarity in the earlier sub-samples, we present the cointegration results two ways. The first set of results shows the unconditional posterior probabilities of cointegration for each pair or trio of future prices for each of our four sub-periods. The second set of results presents conditional posterior probabilities of cointegration where the conditioning is on the presence of non-stationarity; that is, these results are the probability of cointegration conditional on the series being non-stationary. By construction, the conditional posterior probabilities are much larger than the unconditional since they are equal to the unconditional probability of cointegration divided by the probability of the series being non-stationary.

The unconditional results in the left half of the table show that the posterior probability of cointegration increases for every pair and trio in our study as we move from the pre-commodity index fund period to the later sub-samples. While the probability of cointegration generally remains low in all cases, never reaching a majority, the direction of change in the probabilities is clear. However, when the conditional probabilities of cointegration in the right half of the table are examined a different picture emerges. Eight of the eleven pairs and trios show declines in the posterior probability of cointegration when it is conditional on non-stationarity and none of the three that increase show large increases. When combined with the unconditional cointegration results, what this shows is that the increase in the unconditional probability of cointegration is due entirely to the increase in the probability of non-stationarity in the individual future price series.

There is no increase in the probability of shared trends or equilibrium long-run relationships when we control for the changes in the probability of non-stationarity. The cointegration test results provide no evidence in favor of any impact of commodity index funds on the linkages between futures markets. However, it is worth noting that if the commodity index funds are simply buying commodities in fixed proportions (dictated by the basket weights specified in many of their prospectuses), such buying behavior would not tend to induce cointegration where it did not previously exist since buying of that sort does not revolve around any long-run equilibrium relationship nor arbitrage-style elimination of deviations from such an equilibrium.

Summary and Conclusions

In this paper we investigated whether the growth in the size of commodity index funds over the past eight years has caused impacts in commodity futures markets that we can observe through changes in the dynamic behavior of the time series of futures prices. The empirical evidence we uncover is mixed. Examining the behavior of pairs and trios of futures prices, we find significant changes in the correlation coefficients of many pairs of futures prices including those of series without much rationale for being linked. All the changes in correlation that are statistically significant are in the direction of more strongly positive correlation which is exactly the behavior that would be expected from a new long-only buyer purchasing contracts in a fixed basket of (virtually) all commodities. We also find strong empirical evidence in favor of increased non-stationarity in the studied commodity futures prices, which could be caused by the increased volume brought about by the participation of the commodity index funds or by those same funds using some amount of market timing in their purchases.

The empirical evidence shows no increase in cointegration over time. While this is not direct evidence in favor or against the impact of commodity index funds, it would be consistent with funds buying futures contracts in fixed proportions as they get new investments without regard for which commodities are good buys at that particular time. In combination with our results on correlation coefficients and non-stationarity, these empirical results are indicative, but not fully convincing, of the growth of commodity index funds impacting commodity futures market linkages over the last eight years. While this result is somewhat opposite to Sanders and Irwin (2010), the difference is not that great when one considers the moderate strength of our results and the fact that our attribution of the empirical changes observed to commodity index funds is based solely on the time periods examined, not on any concrete evidence.

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Table 1: Futures Contracts

	Contract Months	Contract Size	Price Quotation	Expiration
Corn	3,5,7,9,12	5,000 bushels	¢/bushel	Last business day before the 15^{th} of contract month
Soybeans	1,3,5,7,8,9,11	5,000 bushels	¢/bushel	Last business day before the 15^{th} of contract month
Live Cattle	2,4,6,8,10,12	40,000 pounds	¢/pound	Last business day of contract month
Feeder Cattle	1,3,4,5,8,9,10,11	50,000 pounds	¢/pound	Last Thursday of contract month
Lean Hogs	2,4,5,6,7,8,10,12	40,000 pounds	¢/pound	10^{th} business day of contract month
Cotton	3,5,7,10,12	50,000 pounds	¢/pound	17 business days before the end of contract month
Cocoa	3,5,7,9,12	10 metric tons	$/metric ton	11 business days before the end of contract month
Crude Oil	All months	1,000 barrels	$/barrel	3^{rd} business day before the 25^{th} of month preceding delivery

Table 2: Summary Statistics (1990-2011)

	Mean	Standard Deviation	Minimum	Maximum
Corn	295.767	119.939	180.250	757.500
Soybeans	711.308	250.747	421.000	1,605.000
Live Cattle	78.396	12.597	57.350	122.150
Feeder Cattle	89.662	17.300	50.975	140.520
Lean Hogs	63.909	12.028	28.550	102.775
Cotton	67.126	23.938	29.900	200.230
Cocoa	1,599.306	668.748	704.000	3,757.000
Crude Oil	39.788	27.581	11.220	140.000

Table 3: Posterior Probabilities of Stationarity

	1990-2003	1990-2008	1990-2011	2004-2011
C-CT	0.854	0.666	0.668	0.218
C-S	0.839	0.617	0.600	0.564
C-LH	0.868	0.686	0.695	0.400
C-LC	0.800	0.407	0.259	0.328
C-CL	0.861	0.507	0.552	0.686
CC-CL	0.842	0.553	0.503	0.622
S-LH	0.822	0.821	0.682	0.424
LC-FC	0.791	0.438	0.186	0.212
C-S-LH	0.769	0.592	0.532	0.310
C-LC-FC	0.748	0.318	0.145	0.156
C-CC-CT	0.784	0.509	0.470	0.140

Table 4: Correlation Coefficients

	1990-2003	1990-2008	1990-2011	2004-2011
C-CT	0.469	0.254	0.634	0.757
C-S	0.723	0.883	0.913	0.910
C-LH	0.435	0.281	0.490	0.448
C-LC	-0.220	0.400	0.662	0.754
C-CL	-0.238	0.622	0.731	0.757
CC-CL	0.050	0.690	0.783	0.631
S-LH	0.481	0.301	0.454	0.296
LC-FC	0.717	0.870	0.912	0.794
C-FC	-0.610	0.146	0.489	0.450
C-CC	0.192	0.661	0.760	0.767
CC-CT	0.037	-0.042	0.414	0.638

Table 5: Bayesian Cointegration Test Results

	Unconditional Posterior Probability of Cointegration				Conditional Posterior Probability of Cointegration			
	1990-2003	1990-2008	1990-2011	2004-2011	1990-2003	1990-2008	1990-2011	2004-2011
C-CT	0.097	0.149	0.142	0.162	0.664	0.445	0.430	0.208
C-S	0.094	0.233	0.211	0.147	0.587	0.607	0.529	0.337
C-LH	0.085	0.130	0.118	0.187	0.649	0.415	0.385	0.312
C-LC	0.077	0.185	0.218	0.305	0.386	0.311	0.294	0.454
C-CL	0.052	0.106	0.085	0.067	0.375	0.216	0.191	0.213
CC-CL	0.111	0.189	0.254	0.169	0.699	0.422	0.511	0.449
S-LH	0.064	0.069	0.124	0.179	0.359	0.385	0.391	0.310
LC-FC	0.120	0.219	0.373	0.247	0.574	0.391	0.458	0.313
C-S-LH	0.032	0.070	0.097	0.102	0.140	0.172	0.207	0.148
C-LC-FC	0.033	0.113	0.226	0.160	0.133	0.166	0.264	0.190
C-CC-CT	0.042	0.071	0.080	0.093	0.194	0.145	0.151	0.108