AJAE Appendix: The Commodity Terms of Trade, Unit Roots, and Nonlinear Alternatives*

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Abstract

This appendix contains diagnostic test results and supplemental regression results from an evaluation of the Prebisch-Singer Hypothesis that applies smooth transition autoregressions (STARs) to relative prices for 24 primary commodities.

Keywords: Nonlinear model; Primary commodities; Smooth transition autoregression; Time-varying autoregression; Unit root tests

JEL Classification Codes: O13; C12; C22; C52

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Data

In the empirical analysis we use annual data on prices for 24 primary commodities spanning 1900–98. Nominal prices are deflated by the United Nations Manufactures Unit Value index. The original data set through 1986 was used by Grilli and Yang (1988) to develop their commodity price index. The data were extended through 1998 by Cashin and McDermott (2002), and were used recently by Kellard and Wohar (2006) and Kim *et al.* (2003). More recently, Pfaffenzeller, Newbold, and Rayner (2007) provide updated individual commodity price data for the 1986–98 period and new data for the 1999–03 period. In our empirical analysis, however, we continue to use data through 1998. We do this for several reasons. First, we wish to conduct some simple *ex ante* evaluations of our estimated models predictive performance. Five year's worth of data seems to be minimally sufficient for this purpose. Second, much prior work on this topic has been conducted using data for the 1900–98 sample period. Therefore our results will be more directly comparable with those in the existing literature. In any event, the empirical analysis is conducted on the natural logarithms of the various (relative) price indices. Plots of the basic data, 1900-2003, are reported in figure 1.

Results

Linear Unit Root Tests

The analysis begins with an examination of the linear unit root hypothesis, that is, with tests for a single unit root against an alternative that is stationary in the levels. To this end we compute augmented Dickey–Fuller (ADF) tests for the case where the model includes an intercept but may or may not include a linear trend (i.e., the t_τ and t_μ test statistics, respectively) (Dickey and Fuller, 1979, 1981). Specifically, models similar to (1) in Balagtas and Holt (forthcoming) are estimated for each commodity with and without a trend term. In each case the AIC is used to choose the optimal lag length up to a maximum of six lags. Approximate p–values are constructed by performing B=999 dynamic, non–parametric bootstrap simulations. The results are recorded in table 1.

Based on the preliminary evidence in table 1, there is substantial support for the unit root hypothesis. For example, in the case where the trend is excluded the null hypothesis is rejected at the 5% level for only tobacco and zinc. If a trend is included, the hypothesis is rejected at the 5% level for rubber and at the 10% level for aluminum, wheat, and zinc. While there is some discrepancy in results depending on whether a trend is included, the overall picture emerging from table 1 is one of general support for the unit root hypothesis in commodity prices. This conclusion is, moreover, largely consistent with results reported by, for example, Kim *et al.* (2003) and Kellard and Wohar (2006), among others.

Estimated STAR–Type Models

In Balagtas and Holt (forthcoming) we test for and, where appropriate, estimate members of the family of smooth transition autoregressions, or TVARs. Of course model estimation is only a preliminary part of the modeling cycle used to fit and assess the performance of the fitted models. Here, we employ the diagnostic methods–in the form of LM tests–described by Eitrheim and Teräsvirta (1996) to evaluate the estimated models for: (1) remaining additive nonlinearity and (2) remaining autocorrelation.[1] In order to conduct tests for remaining nonlinearity we reserve the first six observations, that is, we use $s_t = \Delta y_{t-1}, \ldots, \Delta y_{t-6}$ as candidate transition variables. The result is there are 92 observations available for model estimation and diagnostic testing. A summary of diagnostic test results for the final version of the fitted models are recorded in Table 2. Plots of the estimated transition functions, both with respect to the identified transition variable and with respect to time, are displayed in, respectively, the left–hand and right–hand panels of figure 2.

To begin, initial results revealed that in a handful of instances STAR–type models were

[1]Because overall sample sizes are relatively small, we only consider alternatives to first–order STAR–type model specifications that include a second additive term.

inappropriate. Specifically, for cocoa, rubber, and zinc the estimated nonlinear models fail to improve on the fit of their linear counterparts as indicated by the AIC.[2] In each instance this seems to be a result of the identified nonlinearity stemming from a relatively small number of outliers. We therefore restrict our attention to the remaining sixteen commodities.

As indicated in table 2, the estimated STAR–type models apparently fit the data reasonably well. For example, as indicated by the ratio of the standard error of the fitted STAR–type model to its linear counterpart, that is, by, $\widehat{\sigma}_{NL}/\widehat{\sigma}_{L}$, all estimated STAR–type models provide an improvement relative to the linear ones (table 2). In some cases, for example, cotton, lamb, silver, sugar, and tobacco the improvement in fit is substantial. In six instances the error distribution of the estimated residuals departs significantly from normality, specifically, in the case of aluminum, beef, lamb, silver, tea, and tin. In every case this violation is linked to excess kurtosis. As well, there is virtually no evidence of remaining residual autocorrelation at four lags (table 2).

Diagnostic tests of remaining nonlinearity were also performed where where up to six lags, d, of the transition variable $s_t = \Delta y_{t-d}$ are used as candidates. These results are also recorded in table 2. There is little evidence of remaining nonlinearity in the estimated STAR–type models. While there is some evidence of remaining nonlinearity at the 5% level for beef, lead, palmoil, sugar, tea, and tobacco, attempts to fit additional nonlinear components for these commodities yielded no significant improvements. Only for cotton and tobacco is the null hypothesis of parameter constancy clearly rejected. But again, attempts to fit a time varying component to cotton resulted in no improvement in fit as measured by AIC. Overall, the diagnostic test results suggest that the STAR-type models estimated in Balagtas and Holt (forthcoming) provide a reasonable fit to the data.

[2]For these commodities cocoa is associated with a positive drift term while rubber and zinc are associated with negative drift terms. In each case, however, the drift terms are statistically insignificant at all usual levels. Likewise, an results for the alternative models (i.e., the models that imply that the data are trend stationary) revealed that in each of these cases the trend term is not statistically significant. There is therefore apparently little support for the PS hypothesis for these commodities as well.

Model Simulations

While the foregoing results provide ample evidence of nonlinearity and, in some cases, parameter nonconstancy for a relatively large number of commodities in the sample data, the basic question still remains. Is there evidence that the PS hypothesis holds among the commodities for which STAR–type models are fitted? While there are several ways to investigate this issue, one approach is to examine forward iterations of each model, possibly where stochastic shocks are introduced. That is, what is required are the k–step–ahead forecasts from the estimated models using the ending points of the sample data as initial values.

There are at least two reasons for performing forward simulations of the estimated models. First, and as already mentioned, such simulations will reveal something about the role of the PS hypothesis among commodities for which STAR–type models have been estimated. But of equal importance, forward extrapolations of the model will reveal something about its dynamic properties. Indeed, a necessary condition for stability of an estimated STAR model is that forward iterations of its "skeleton," that is, the forward iterations that do not include stochastic shocks and therefore result in biased forecasts, either converge to a steady–state or a limit cycle path (Tong, 1990). Alternatively, a necessary and sufficient condition for stability is that the forward iterations of the model obtained when shocks are included, that is, the unbiased forecasts, converge to a stable path (Tong, 1990). In this manner useful information may be obtained about each model's dynamic properties.

For the nonlinear models being considered, that is, for the STAR and TV–STAR models, analytical expressions for the forecasts are not available for forecast horizons $k \geq 2$.[3] Therefore, numerical methods must be employed. To see this, let the candidate nonlinear model, rewritten in levels form, be represented by

$$(1) \qquad y_t \; = \; f(y_{t-1}, \ldots, y_{t-p-1}; \boldsymbol{\theta}) + \varepsilon_t, \;\; t = 1, \ldots, T,$$

[3]Because TVAR models do not involve nonlinearity in lagged values of the dependent variables, forecasts from these models may be obtained analytically, and therefore require no special attention.

where $\boldsymbol{\theta}$ is a parameter vector and $\varepsilon_t \sim iid(0, \sigma^2)$. Multiple–step–ahead forecasts are desired from (1) for the period $T+1, \ldots, T+M$, $M \geq 1$. To begin, the one-step-ahead forecast of y_t may be obtained analytically as

$$(2) \qquad \widehat{y}_{T+1|T} \;=\; f(y_T, \ldots, y_{T-p}; \boldsymbol{\theta}),$$

where the usual assumption $E(\varepsilon_{T+1}|\boldsymbol{\Psi}) = 0$ has been applied, and where $\boldsymbol{\Psi}$ denotes the history $y_T, y_{T-1}, \ldots$ of observations on y_t. For forecasts at horizons $k \geq 2$, analytical results are no longer available. For example, suppose that we desire a forecast at horizon $k = 2$. We then have

$$(3) \qquad \widehat{y}_{T+2|T} \;=\; \int_{-\infty}^{\infty} f(\widehat{y}_{T+1|T} + \varepsilon_{T+1}, y_T, \ldots, y_{T-p}; \boldsymbol{\theta}) d\varepsilon_{T+1},$$

To solve (3) numerical integration techniques must be employed. If forecasts at horizons $k > 2$ are desired, computing the forecast will involve multidimensional numerical integration. At this point several methods may be applied, including Monte Carlo integration and bootstrapping. Here we use the bootstrap method explored originally by Clements and Smith (1997). The requirement is, of course, that the error terms in (1) be independent.

To implement the bootstrap algorithm we simulate N paths for $y_{T+1}, y_{T+2}, \ldots, y_{T+k_{max}}$. For present purposes we set $N = 1000$ and $k_{max} = 200$. We then obtain forecasts for horizons $k \geq 2$ by averaging across all N paths. At horizon $k = 2$, for example, we have

$$(4) \qquad \widehat{y}_{T+2|T} \;=\; \frac{1}{N}\sum_{i=1}^{N} \widehat{y}_{T+2|T}(i) \;=\; \frac{1}{N}\sum_{i=1}^{N} f(\widehat{y}_{T+1|T} + \widehat{\varepsilon}_i, y_T, \ldots, y_{T-p}; \boldsymbol{\theta}),$$

where $\widehat{\varepsilon}_i$ denotes an estimated residual from (1) sampled with replacement up to time period T. A naïve forecast or forward simulation may be obtained by simply setting $N = 1$ and $\widehat{\varepsilon}_i = 0$. The latter amounts to nothing more than a deterministic extrapolation of the so–called "skeleton" of the model.

The forward simulations obtained for each of the sixteen STAR–type models, along with the historical sample data, are presented in figure 2 of Balagtas and Holt (forthcoming).

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Table 1: Results of Dickey–Fuller Tests Applied to 24 Commodities

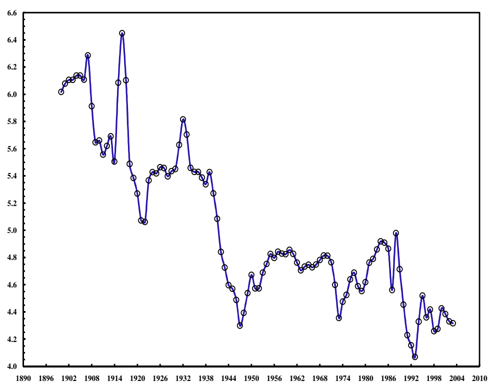
	No Trend under the Alternative			Trend under the Alternative		
Commodity	$\widehat{\rho}$	$t_{\widehat{\mu}}$	p–value	$\widehat{\rho}$	$t_{\widehat{\tau}}$	p–value
Aluminum	0.934	-2.344	0.239	0.801	-3.175	0.088*
Bananas	0.912	-1.812	0.368	0.882	-2.304	0.423
Beef	0.930	-1.892	0.331	0.822	-2.823	0.202
Cocoa	0.872	-2.281	0.171	0.867	-2.334	0.404
Coffee	0.816	-2.677	0.185	0.807	-2.640	0.285
Copper	0.857	-2.072	0.185	0.855	-2.061	0.496
Cotton	0.985	-0.360	0.905	0.871	-1.988	0.574
Hides	0.837	-2.107	0.249	0.643	-2.995	0.148
Jute	0.902	-1.292	0.674	0.846	-1.875	0.628
Lamb	0.920	-1.960	0.283	0.791	-3.050	0.137
Lead	0.899	-1.402	0.537	0.850	-1.902	0.634
Maize	0.956	-0.671	0.873	0.672	-2.978	0.130
Palm Oil	0.926	-1.216	0.686	0.746	-2.694	0.221
Rice	0.946	-1.110	0.684	0.798	-2.536	0.277
Rubber	0.920	-2.181	0.164	0.765	-3.602	0.043**
Silver	0.911	-1.839	0.337	0.898	-2.022	0.564
Sugar	0.840	-1.795	0.390	0.693	-2.627	0.305
Tea	0.909	-1.676	0.429	0.877	-2.091	0.537
Timber	0.902	-2.222	0.181	0.736	-3.386	0.054*
Tin	0.879	-2.514	0.121	0.895	-1.813	0.686
Tobacco	0.911	-2.779	0.027**	0.909	-1.702	0.624
Wheat	0.974	-0.438	0.894	0.633	-3.099	0.068*
Wool	1.024	0.622	0.995	0.879	-1.701	0.682
Zinc	0.536	-3.075	0.021**	0.531	-3.072	0.087*

Note: $\widehat{\rho}$ is the estimated root. The test statistics $t_{\widehat{\mu}}$ and $t_{\widehat{\tau}}$ are t–ratios for $(\widehat{\rho} - 1)$, and correspond, respectively, to: (1) the case where the estimated model does not include a trend, and (2) the case where the estimated model does include a linear trend. Columns headed p–value record approximate p–value's based on $B = 999$ bootstrap simulations. A superscripted * indicates significance at the 10% level, ** significance at the 5% level and, *** significance at the 1% level.

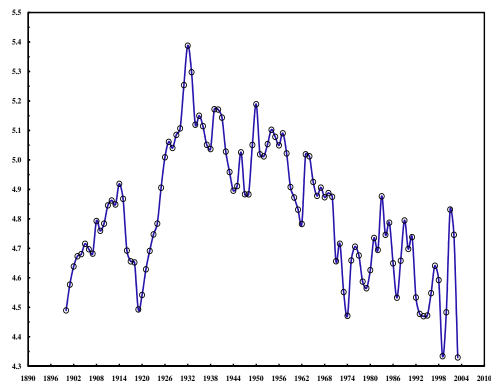
Table 2: Diagnostic Test Results for Estimated STAR–type Models

									Tests for Remaining Nonlinearity/Parameter Constancy						
Commodity	$\widehat{\sigma}_{\varepsilon}$	AIC	R^2	$\widehat{\sigma}_{NL}/\widehat{\sigma}_L$	SK	EK	LJB	LM_{AR}	Δy_{t-1}	Δy_{t-2}	Δy_{t-3}	Δy_{t-4}	Δy_{t-5}	Δy_{t-6}	t
Aluminum	0.136	-3.643	0.353	0.851	0.760	4.216	79.77(4.77E-18)	0.704	0.068	0.170	0.613	0.799	0.477	0.176	0.133
Beef	0.213	-2.922	0.170	0.929	0.015	1.956	14.90(0.001)	0.127	0.050	0.622	0.005	0.757	0.215	0.816	0.130
Coffee	0.230	-2.761	0.202	0.951	0.054	0.419	1.51(0.470)	0.535	0.658	0.763	0.138	0.583	0.489	0.976	0.752
Copper	0.140	-3.677	0.259	0.927	0.001	-0.407	0.652(0.722)	0.619	0.981	0.479	0.974	0.321	0.673	0.135	0.624
Cotton	0.115	-3.914	0.496	0.780	0.068	-0.220	1.23(0.541)	0.134	0.887	0.256	0.055	0.654	0.569	0.736	0.025
Hides	0.211	-2.807	0.375	0.897	0.037	0.004	0.561(0.756)	0.863	0.874	0.424	0.155	0.753	0.878	0.882	0.218
Lamb	0.173	-2.966	0.500	0.781	0.205	1.927	17.37(1.69E-4)	0.218	0.602	0.211	0.373	0.215	0.149	0.388	0.863
Lead	0.135	-3.694	0.384	0.824	0.001	-0.164	0.118(0.943)	0.734	0.192	0.697	0.592	0.016	0.289	0.253	0.258
Palmoil	0.178	-3.106	0.378	0.877	0.002	0.773	2.33(0.312)	0.714	0.101	0.042	0.351	0.482	0.602	0.057	0.076
Silver	0.140	-3.586	0.458	0.786	0.199	0.900	6.16(0.046)	0.080	0.200	0.214	0.333	0.120	0.309	0.062	0.051
Sugar	0.216	-2.518	0.623	0.689	0.131	0.594	3.37(0.186)	0.503	0.798	0.031	0.947	0.843	0.514	0.283	0.683
Tea	0.141	-3.705	0.240	0.930	0.197	1.314	9.63(0.008)	0.476	0.002	0.221	0.281	0.718	0.154	0.760	0.641
Timber	0.106	-4.132	0.382	0.822	0.023	0.826	3.43(0.180)	0.735	0.118	0.563	0.311	0.177	0.754	0.422	0.617
Tin	0.155	-3.554	0.200	0.938	0.381	1.750	17.57(1.53E-4)	0.538	0.863	0.928	0.620	0.460	0.594	0.567	0.259
Tobacco	0.074	-4.738	0.560	0.779	0.040	0.482	1.50(0.473)	0.753	0.025	0.150	0.116	0.619	0.432	0.285	0.022
Wool	0.165	-3.277	0.334	0.907	0.015	0.305	0.590(0.745)	0.505	0.167	0.422	0.750	0.356	0.662	0.819	0.356

Note: $\widehat{\sigma}_{\varepsilon}$ is the residual standard error; AIC is Akaike information criterion; R^2 is the unadjusted R^2, and $\widehat{\sigma}_{NL}/\widehat{\sigma}_L$ is the ratio of the residual standard error from the respective STAR–type model relative to the linear AR model. As well, SK is skewness, EK is excess kurtosis, and LJB is the Lomnicki– Jarque–Bera test of normality of residuals, with asymptotic p–values in parentheses (Lomnicki, 1961; Jarque and Bera, 1980). LM_{AR} denotes the F variant of Eitrheim and Teräsvirta's (1996) LM test of no remaining autocorrelation in the residuals based on four lags. Remaining columns report p–values for F variants of Eitrheim and Teräsvirta's (1996) LM tests for remaining nonlinearity, $(\Delta y_{t-1}, \ldots, \Delta y_{t-6})$, and parameter constancy, t.



Aluminum



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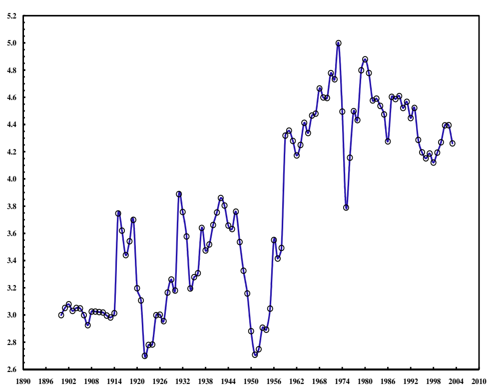

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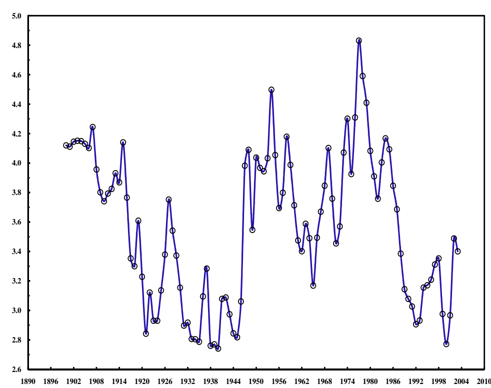

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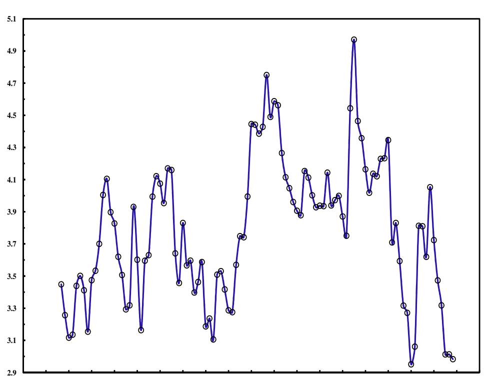

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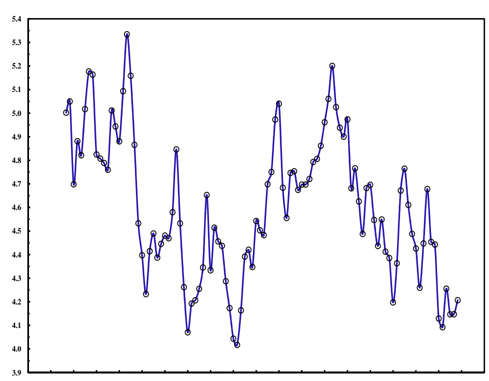

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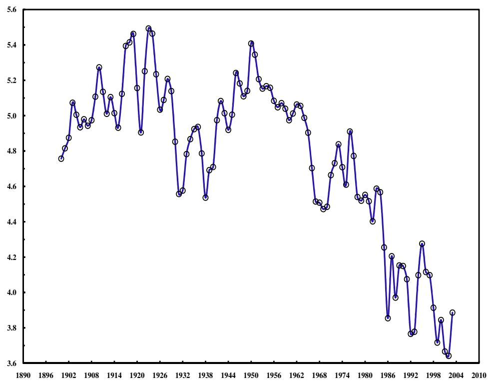

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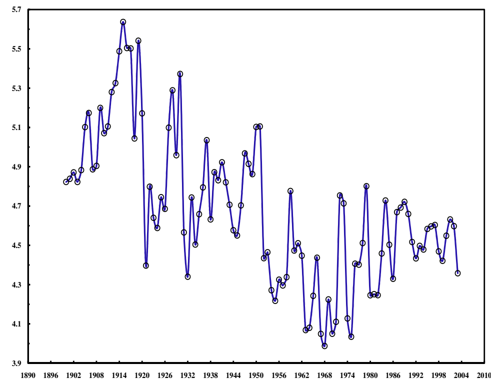

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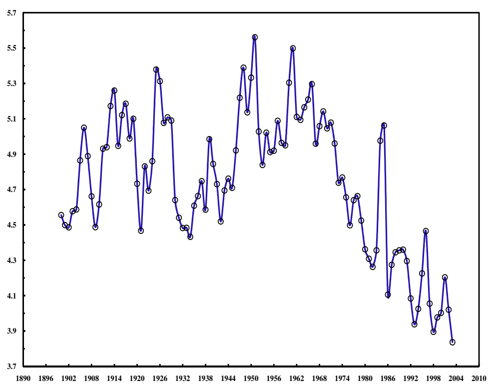
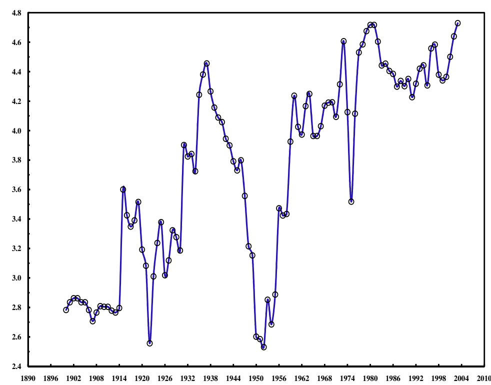


Jute



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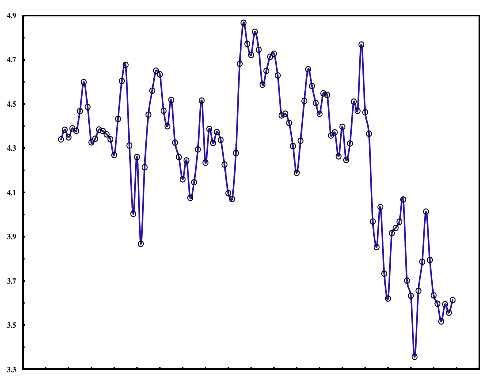

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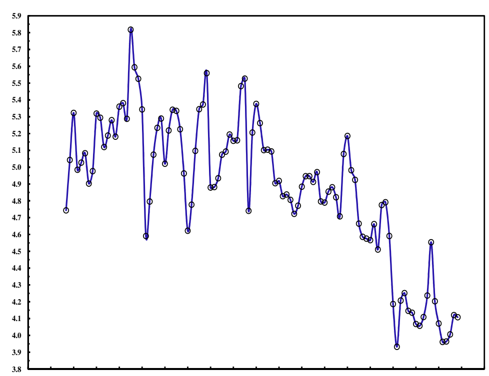

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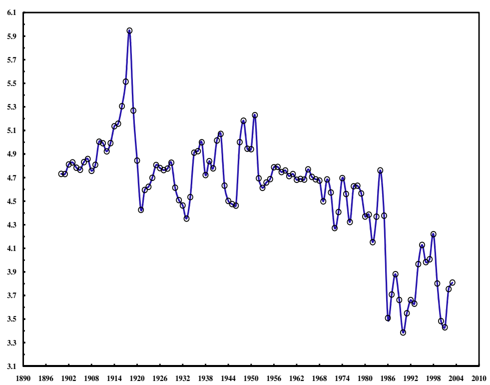

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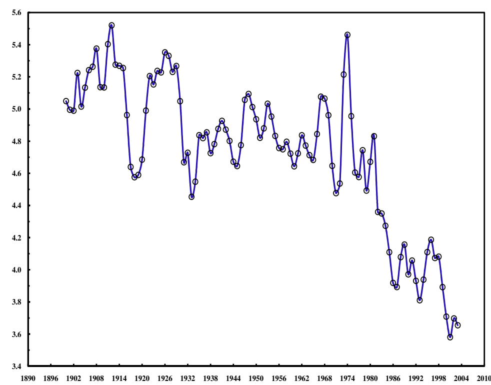

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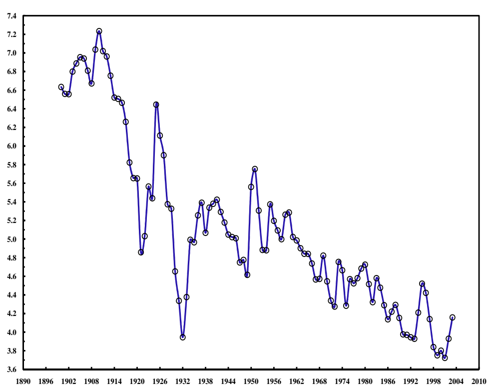
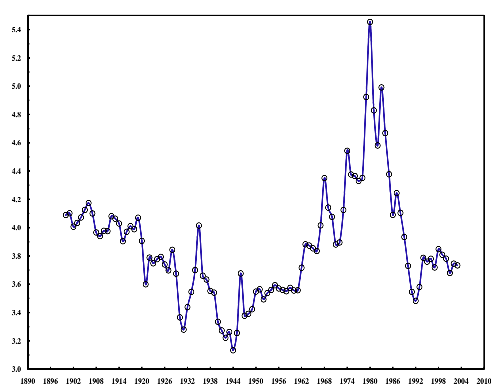


Rubber



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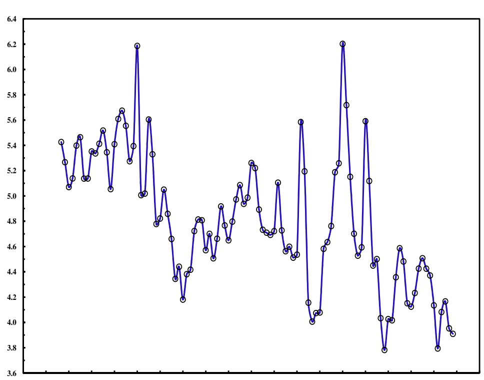

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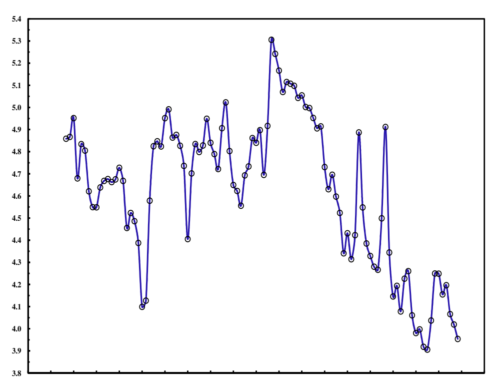


Tea

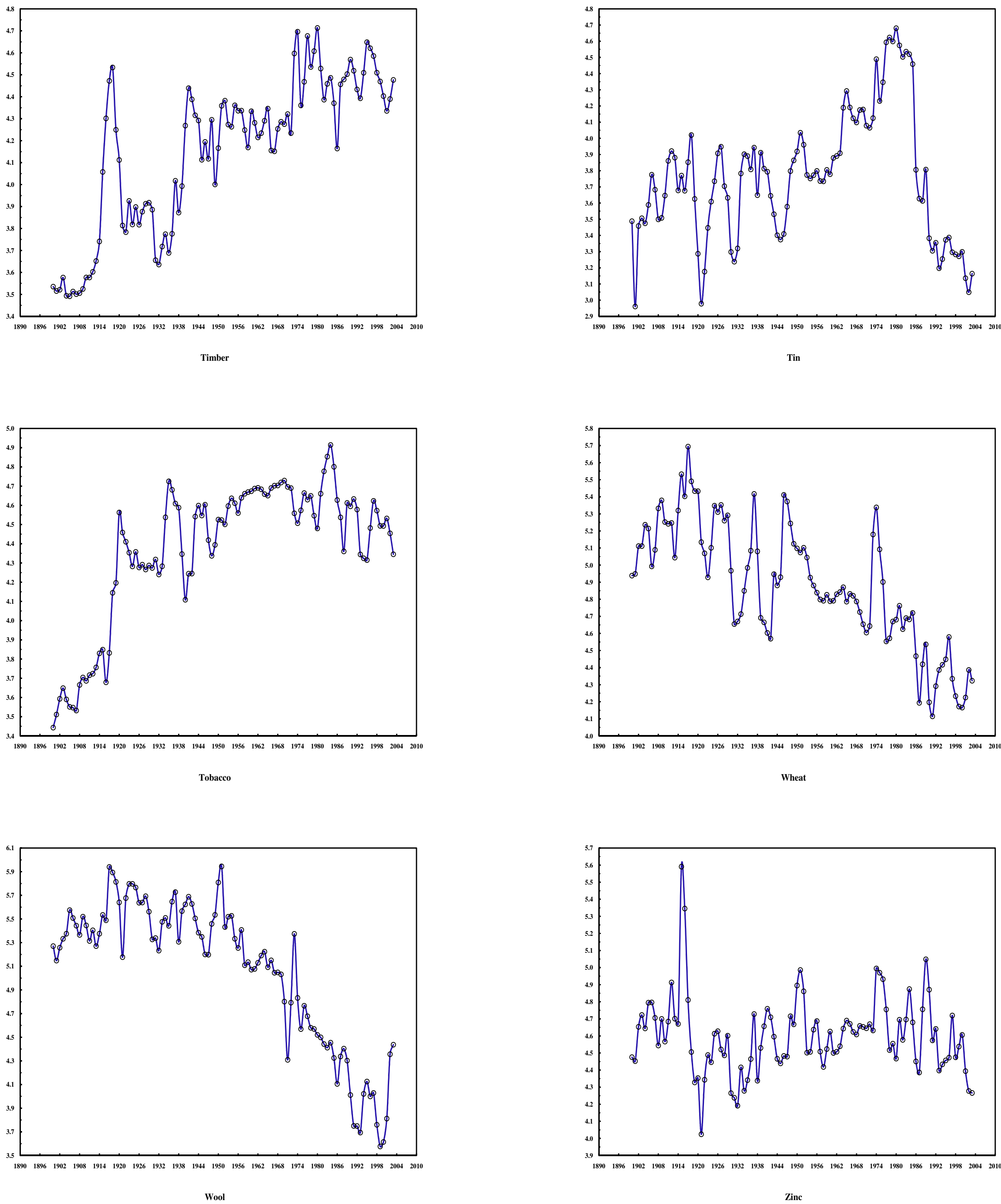
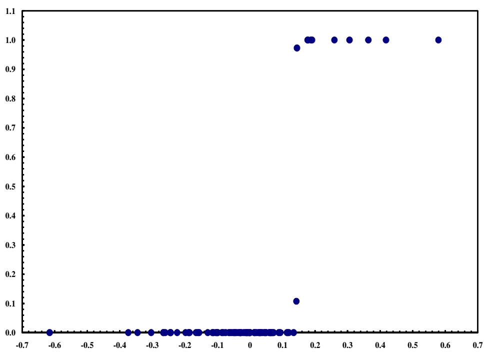


Figure 1: Relative Price Data Plots for 24 Commodities, 1900–2003



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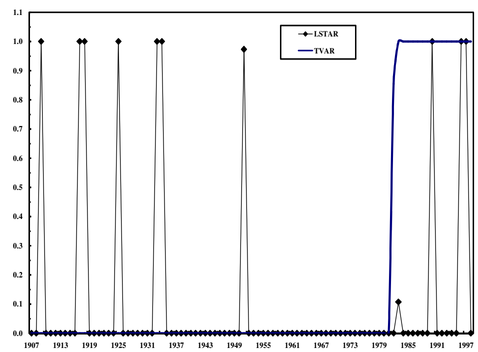

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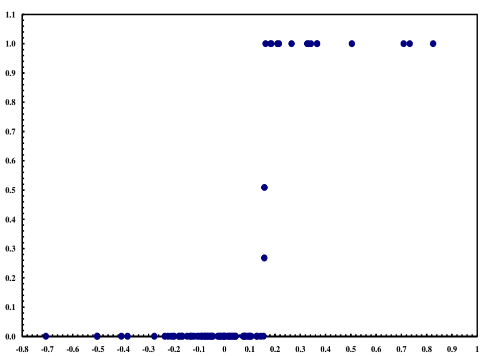

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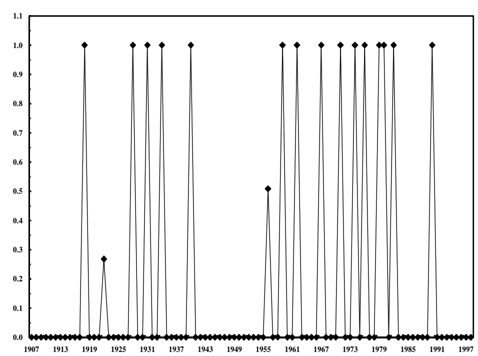

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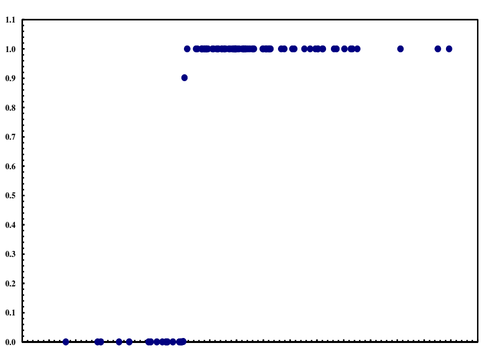

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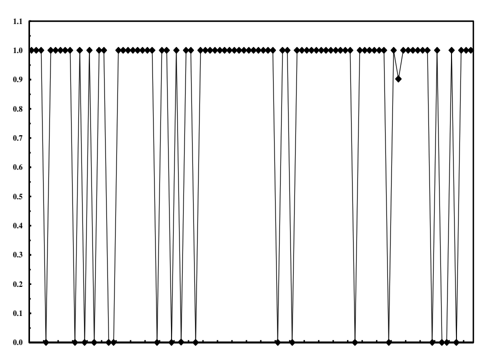

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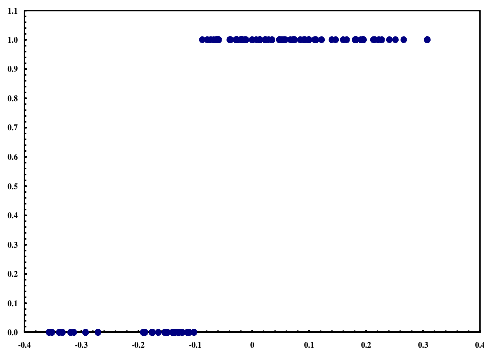

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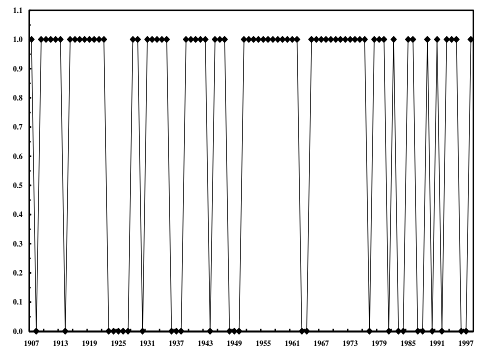

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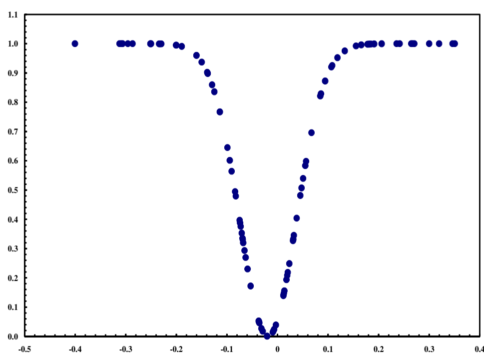

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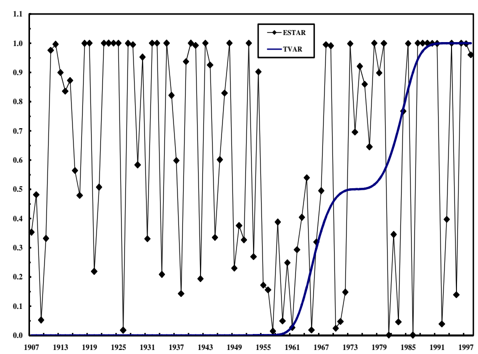

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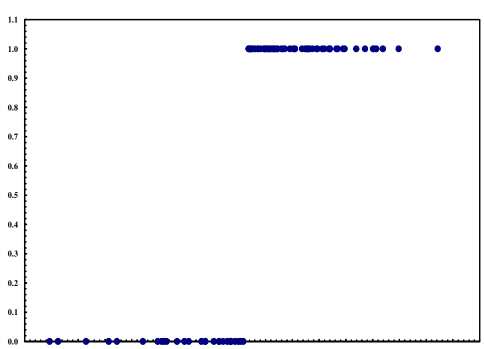

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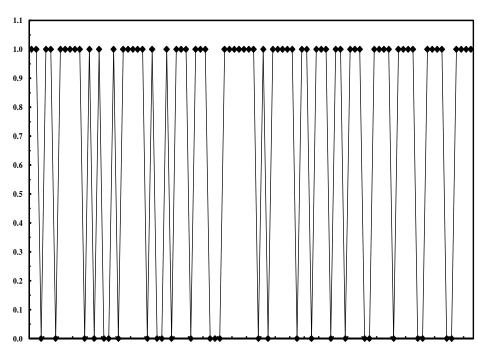

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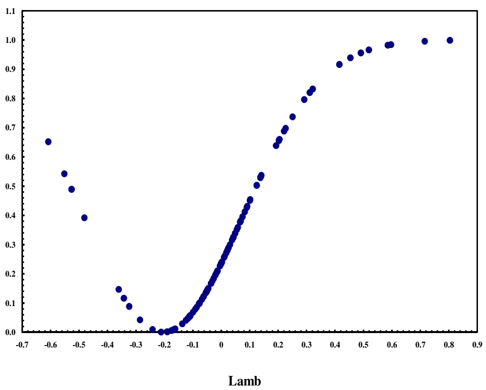
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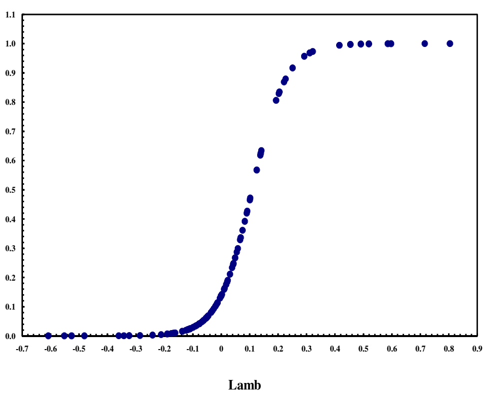
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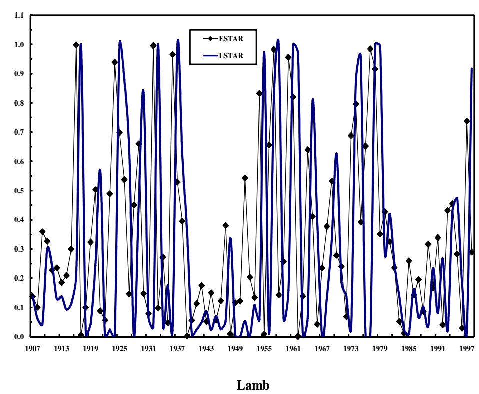
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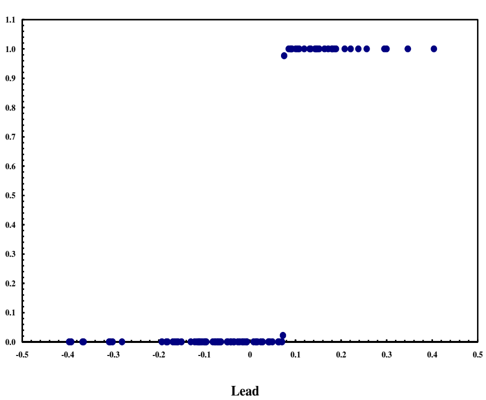
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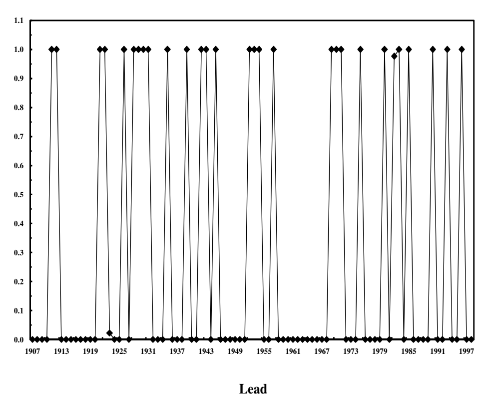
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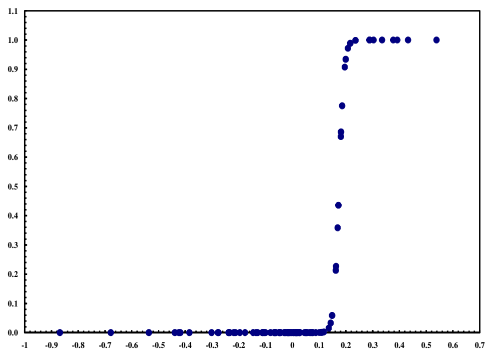

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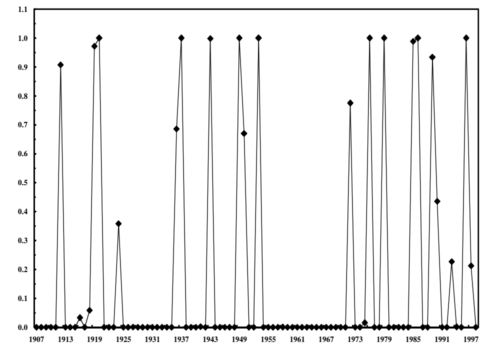

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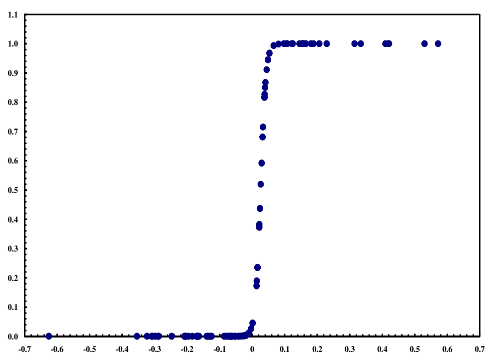

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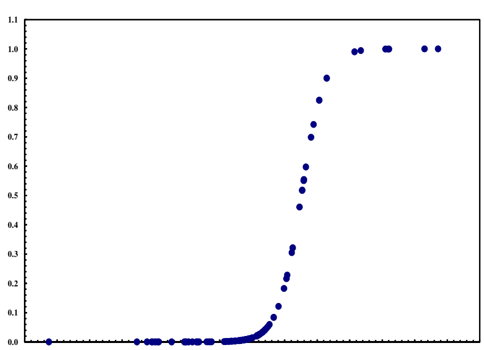

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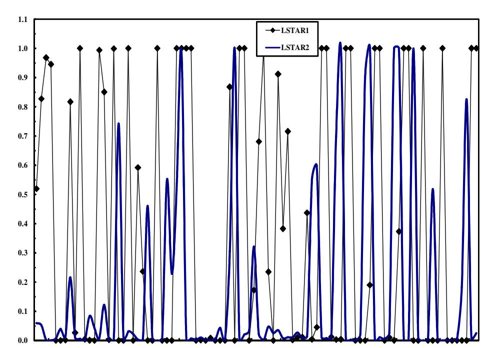

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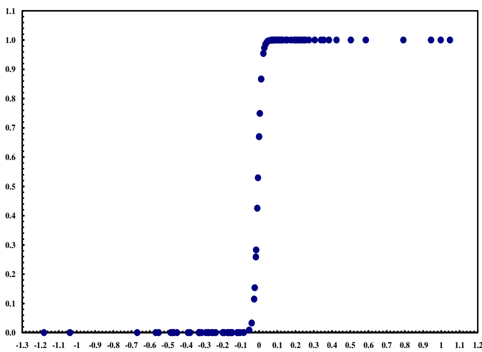

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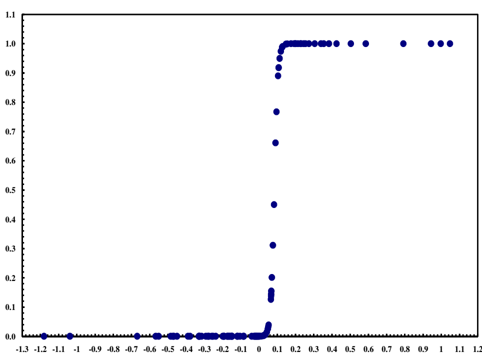

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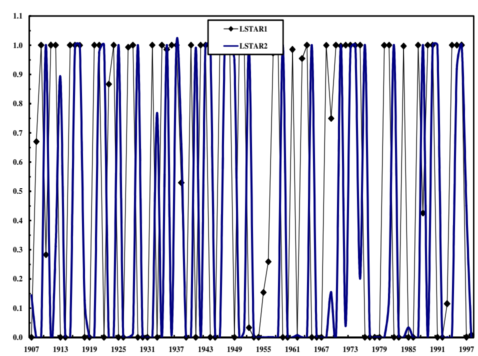

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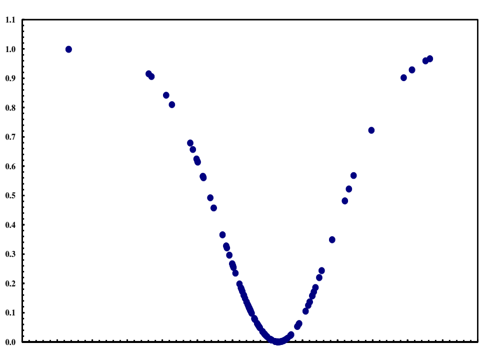

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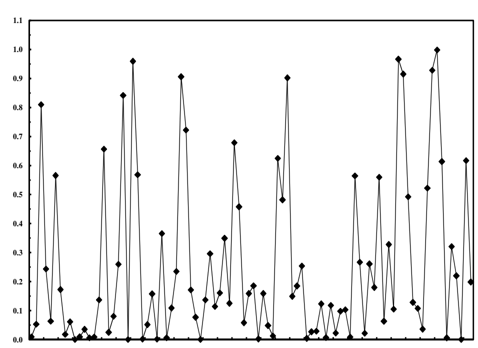

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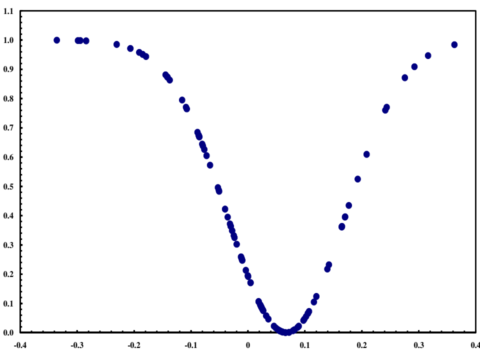

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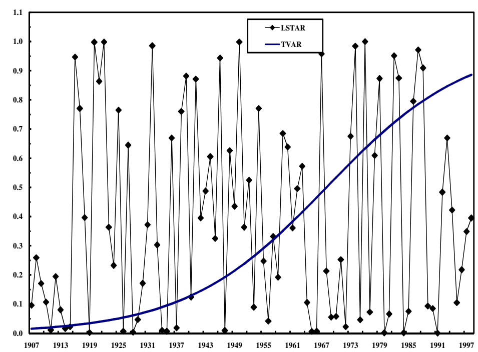

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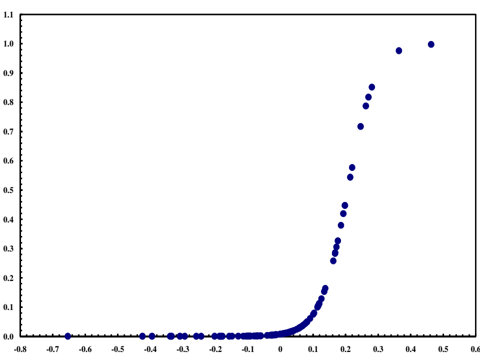

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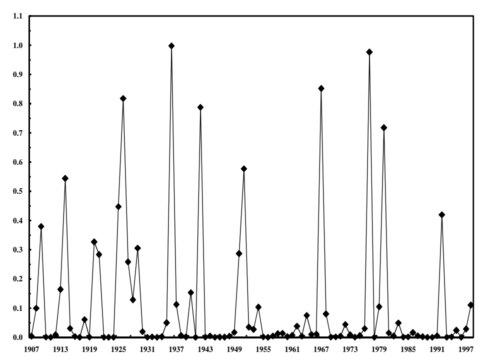

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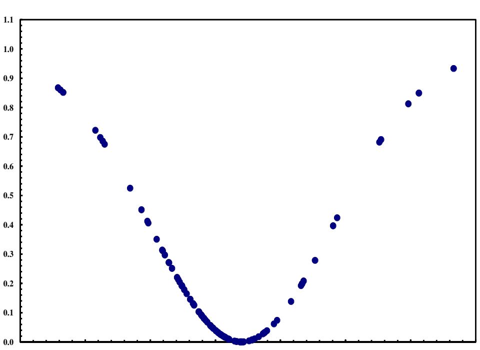

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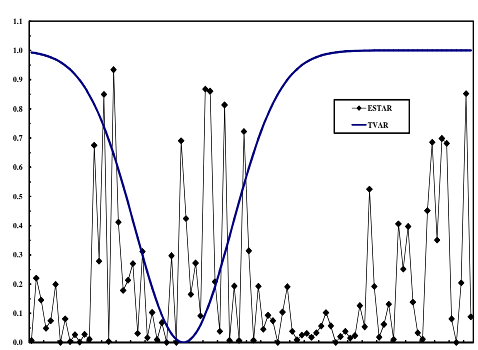

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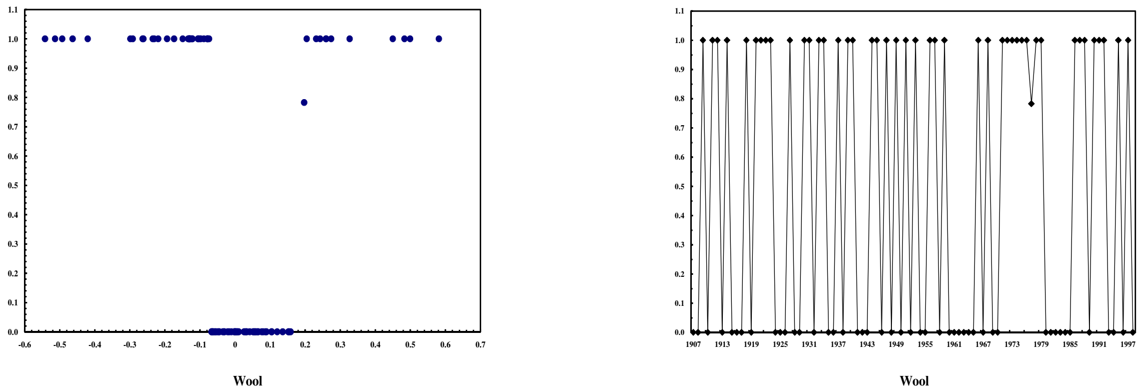

Figure 2: Transition Functions versus the Respective Transition Variable (left–hand column) and Transition Functions Over Time (right–hand column) for 16 Commodities