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ENSO and Soybean Prices: Correlation without Causality

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ABSTRACT

In this paper we seek to characterize the robustness of the ENSO/soybean price relationship and to determine whether it has practical economic content. If such a meaningful relationship exists, the implications could be profound for commodity traders and for public sector investments in climate forecasting capabilities. Also, the validity of economic evaluations of climate impacts and climate forecasts based on ENSO-price independence would come into question. Our findings suggest a relationship between interannual climate and soybean prices, although we are not able to attribute the relationship to ENSO or to say that ENSO is economically important.

Key Words: *climate forecasting, Granger causality, spectral analysis, SOI, SST.*
JEL: C22, Q11.

Recent advances have made it possible to forecast El Niño-Southern Oscillation (ENSO) events with a lead time of several months to a year (Barnston *et al.*; Latif *et al.*; National Research Council 1996, 1999). Research suggests a considerable potential value of ENSO forecasting to agriculture. The value of improved forecasts for agriculture in the southeastern U.S. may exceed $100 million annually (Adams *et al.*), and for the entire U.S., $200 million (Solow *et al.*). Economic studies of the value of ENSO forecasts to agriculture are surveyed by Johnson and Holt, Mjelde et al., and on Katz' internet web site (www.esig.ucar.edu/HP_rick/agriculture.html). To date, researchers evaluating the use of climate forecasts in agriculture have focused on crop yield effects, without considering short-term, feedback effects of ENSO on crop prices. An exception is Keppenne, who identifies an ENSO signal in soybean prices but without characterizing its temporal structure or whether it satisfies conditions for economic causality. Soybean producers, distributors, and consumers can use ENSO forecasts as indicators of future crop prices, but only if the timing and magnitude of the effects are known and only if ENSO forecasts have significant predictive value for soybean prices (Letson *et al.*).

Keppenne analyzed monthly data from 1972:1–1993:4 on soy futures prices and the Southern Oscillation Index (SOI). The SOI data are derived from the sea level pressure data in the following fashion: monthly means and standard deviations are computed for the sea level pressure data, and each monthly observation is recentered and standardized so that the monthly means are zero and the

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monthly standard deviation is zero. The resulting series is first-differenced to produce the SOI. The same monthly standardization is applied to the soy futures prices, but rather than first-differencing, a linear time trend is subtracted. These normalized data are filtered using multichannel singular spectrum analysis with a 48-month window. Keppenne finds the filtered series to be highly correlated and nearly in phase, which strongly suggests the existence of an ENSO signal in soy futures prices. To investigate the possibility that these results are an artifact of the estimation process, Keppenne repeats the analysis after replacing the soy futures data with a simulated AR(1) series and finds no relationship. Keppenne also analyzed corn and wheat, but found no relationship. He hypothesized that government interference in these markets prevents any possible signal from being observed. If a meaningful relationship exists between ENSO and the price of a major commodity such as soybeans, the implications could be profound for buyers and sellers of the commodity and for public sector investments in climate forecasting capabilities. Also, the validity of economic evaluations of climate impacts (e.g., Ferreyra *et al.*) and climate forecasts (e.g., Messina *et al.*) based on ENSO-price independence would come into question.

We seek to characterize the robustness of the ENSO/soybean price relationship over alternative definitions of those variables and to determine whether that relationship has practical economic content. If there really is an ENSO signal in the soy market, it should be amenable to detection using (1) an ENSO index other than SOI, (2) a soy price other than the futures price, and (3) a different methodology. If, for example, a researcher used SOI and the futures price but a different methodology and found no relation, doubt would be cast on Keppenne's result: only one critical element has changed and the result disappears. Contrariwise, if all three elements are changed and the relation still obtains, then strong support has been found for Keppenne's result. Finally, for an ENSO/soybean price signal to have economic value for private and public decision makers, it should satisfy conditions for economic causality.

The effect of ENSO on soy futures prices must be mediated through the effect of ENSO on the supply of and demand for soy. Since supply and demand also affect the spot price, there should also be an ENSO signal observable in the spot price of soy. Moreover, it should be observable using methods other than multichannel singular spectrum analysis and with an ENSO index other than SOI. Thus, we undertake to ascertain whether there is a sea surface temperature anomaly signal in soy spot prices using the traditional methods for the analysis of economic time series, and we do not pre-process the data. We find that such a signal exists, but is so small as not to constitute evidence of causality.

In Section Two we describe the data and apply the usual methods to assist in determining the time series properties of the series: spectral analysis and Box-Jenkins identification. In Section Three, we apply Granger Causality Tests (Granger 1969) to determine whether ENSO does have an effect on soy prices: we find that ENSO does not "cause" soy prices, and vice versa. Section Four presents the conclusions.

Preliminary Analysis

As an ENSO index, we used sea surface temperature (SST) anomalies spatially averaged over the eastern equatorial Pacific Ocean: 4°S–4°N, 150°W–90°W. Alternative ENSO definitions exist based on atmospheric pressure patterns in the tropical Pacific Ocean (Trenberth), and our decision to use an SST measure was partly to test the robustness of Keppenne's findings, which did employ an atmospheric pressure index. For soy prices we used the USDA/NASS prices received by farmers, dollars per bushel (www.nass.usda.gov:81/ipedb/). Table 1 presents some selected observations on our data so interested researchers can correctly identify the data we use.

To analyze the data in the time domain we use the package RATS v4.3 (Doan) running under Windows 2000. Spectral analyses are conducted using the package R v1.30 (Ihaka

Table 1. Selected Observations

Date	SOY	SST
1950:01	2.11	24.1
1950:02	2.12	24.8
1974:01	5.87	23.6
1974:02	6.07	25.0
2000:11	4.55	24.1
2000:12	4.78	24.4

and Gentleman) running under Linux Red Hat v7.1. Graphics have been rendered using R.

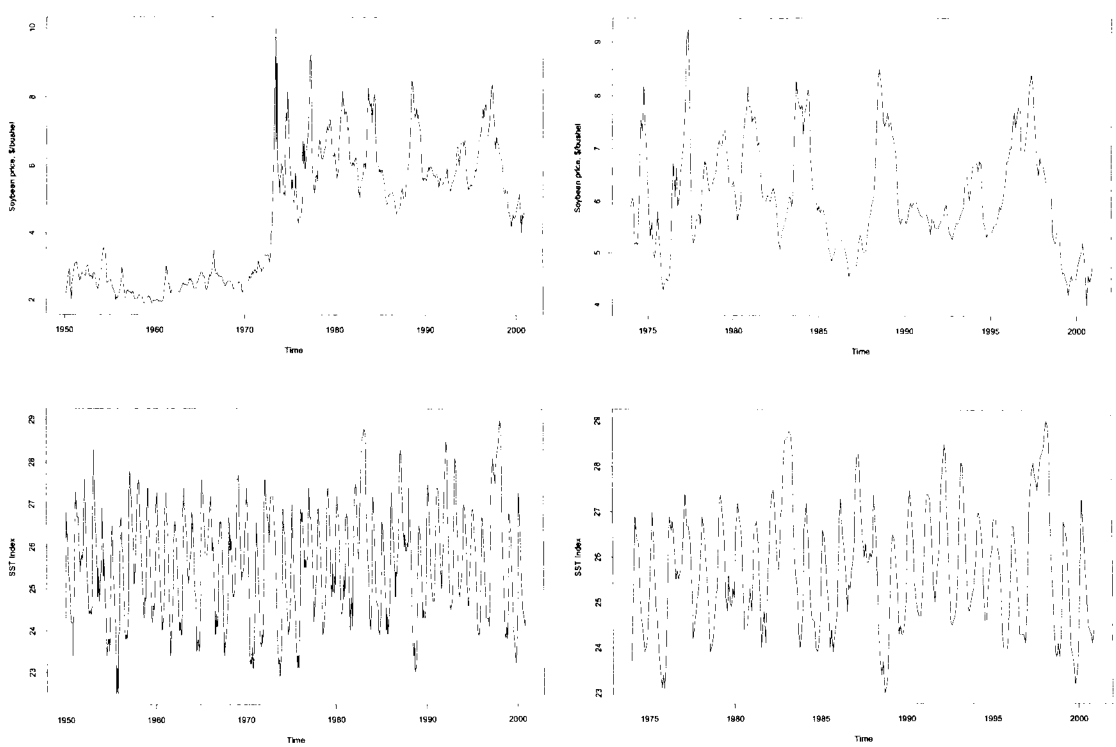
Figure 1 displays the SOY series from 1950 to 2000. Clearly there has been some sort of regime shift in 1972 or 1973 (Glantz, p. 33). For convenience we select the 1974:1–2000:12 period, displayed in Figure 2. No evidence of a time trend is apparent. Regressing SOY on a constant and linear time trend yields:

$$\text{(1)}\quad \begin{array}{ccc} SOY = & c & + \; b\,TIME \\ & 6.89 & -0.0018 \\ & (25.06) & (-2.97) \end{array}$$

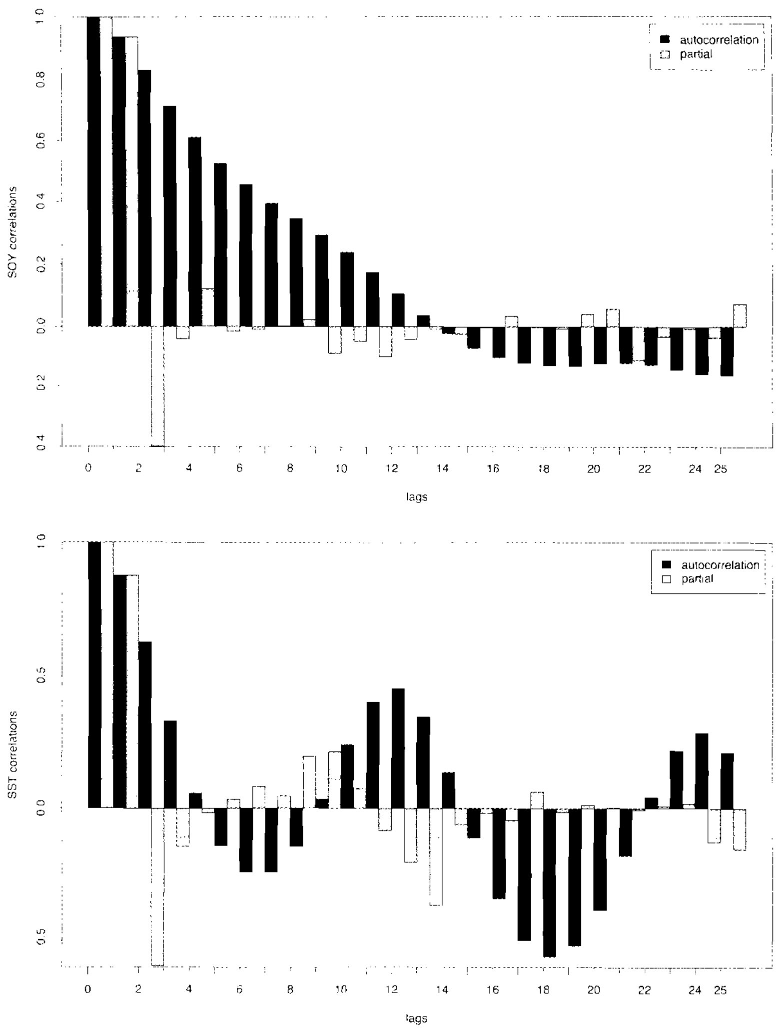
$$R^2 = 0.027 \qquad n = 324$$

where t-statistics are in parentheses. The time trend, though statistically significant, is practically insignificant. Figures 3 and 4 display the SST index over the 1950–2000 and 1974–2000 periods.

Figures 5–6 display autocorrelation (AC) and partial autocorrelations (PAC) for the two series, together with $\pm 2\sqrt{n}$ approximate confidence bands. Since the data are highly correlated, the Yule-Walker equations are not used for these calculations (see McCullough 1998 and the references therein). Instead, we use the linear regression formulation to compute these quantities. The SOY data, with a PAC that cuts off after two lags and an AC that decays, clearly suggest an AR(2) model. The nature of the AC decay suggests a weak 12-month cycle. The SST data present a PAC that cuts off after two lags, with significant lags at 12,13 and 24,25. We computed AC and PAC out to 50 lags for both series, and found none significant beyond those already reported. The sinusoidal nature of both AC and PAC suggest the existence of six- and twelve-month



Figures 1–4. Time series plots of SOY and SST, 1950–2000 and 1974–2000

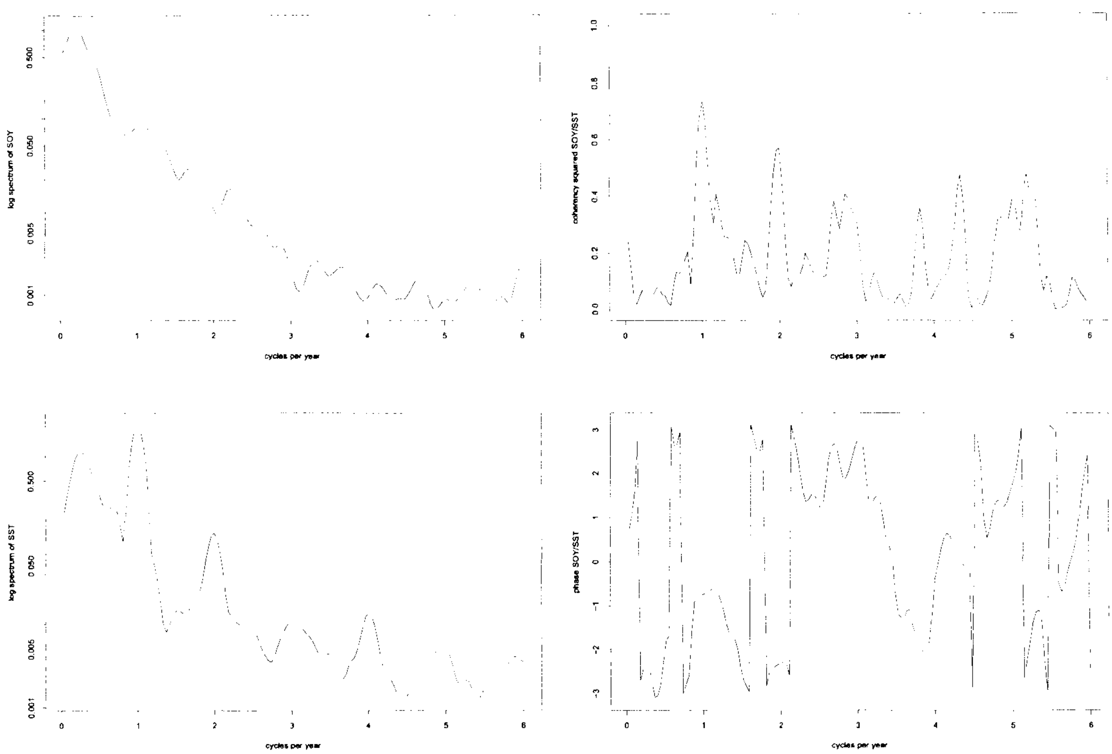


Figures 5–6. Autocorrelations and partial autocorrelations for SOY and SST

cycles. The information provided by the AC/PAC plots will be used to guide the spectral analysis, before which each series is recentered by subtracting its mean. Whether the data are recentered or detrended makes very little difference numerically and makes no difference qualitatively.

The periodograms (not shown) indicate a substantial annual cycle in SST and a barely noticeable annual cycle in SOY. Naturally, we attempted to smooth the periodograms to elicit a peak at the annual cycle. However, the peak at the annual cycle in the periodogram of SOY barely survived modest smoothing. We employed the usual variety of spectral techniques in an exploratory fashion. Our displayed results are based on the following considerations. As 324 is highly composite ($324 = 2^2 3^4$), we do not pad, but we do apply a 10-percent cosine taper. The periodogram is smoothed using a modified Daniell filter with $m = 5{,}5$ (Bloomfield, Section 8.7). The abscissae measure cycles per year which, given the monthly data, implies that the Nyquist frequency is six cycles per year.

The log-spectrum of SOY, Figure 7, is dominated by low-frequency components. In addition to the modest annual peak, there is also a noticeable peak occurring at 0.259 cycles per year, which corresponds roughly to a four-year or 48-month cycle. The log-spectrum of SST, Figure 9, shows clear peaks corresponding to



Figures 7–10. Spectra and cross spectra of SOY and SST

the annual cycle, with the attendant harmonics. There is also the usual peak for a 48-month period, again occurring at 0.259 cycles per year, which corresponds to the frequency of ENSO events (e.g., Sun and Chen).

Since the relation between SOY and SST is of interest, we also consider cross spectral analysis—as we take the Fourier Transform of each series directly, we do not align the two series based on the cross-correlation function. The squared coherency, Figure 8, indicates a substantial peak at the annual cycle, with minor peaks corresponding to the harmonics. Unlike Keppenne, we find no appreciable coherence at the 48-month cycle or at any other cycle that might be construed as an ENSO signal. Only the annual and six-month cycles are statistically significantly different from zero at the 1-percent level, the latter just barely so. Keppenne's result, that ENSO and soy prices are highly correlated and nearly in phase, may apply only to the SOI signal and not to the SST signal. The 99-percent confidence interval for the phase includes the origin at the annual cycle, but for the six month cycle the 99-percent confidence interval is wholly negative. Thus, at the annual cycle, SOY and SST may be in phase. The values of phase near the six-month cycle average to about -2.5; since the phase is negative, this implies that SOY lags SST at this frequency. Whether SST variations in fact "cause" changes in soy prices merits investigation.

Granger Causality

Based on the cross spectral results, it is clear that there is some significant correlation between SOY and SST at one-year cycles. This raises the question of whether the correlation satisfies economic notions of causality, which has testable implications.

The concept of Granger Causality (Granger 1969) has a long history of widespread application in economics. It can be easily explained by use of the bivariate regressions

$$(2) \qquad X_t = \sum_{k=1}^{M_x} a_k X_{t-k} + \sum_{k=0}^{M_y} b_k Y_{t-k} + \epsilon_1$$

$$(3) \qquad Y_t = \sum_{k=0}^{M_x} c_k X_{t-k} + \sum_{k=1}^{M_y} d_k Y_{t-k} + \epsilon_2$$

where M_x is the number of lags in a distributed lag representation of X, and similarly for M_y and Y. Consider the null hypothesis that $b_k = 0$, $k = 1, 2, \ldots, M_b$. If this null hypothesis is rejected, then Y is said to "Granger-cause" X. The name is somewhat of a misnomer, since correlation does not imply causality. However, the test does indicate whether Y has predictive power for X. Similarly, if the c_k in equation 3 are non-zero, then X "causes" Y. For an authoritative discussion see Geweke.

Note that both (2) and (3) allow for "instantaneous causation" by the presence of the b_0 and c_0 coefficients. There is some confusion in the literature concerning these coefficients. Granger (1969, p. 431) originally referred to (2–3) as the "more general model with instantaneous causality" and recommended its use "[I]f the variables are such that this kind of representation is needed." He later recanted (Granger 1988) and argued that instantaneous causality should never be considered, and that only equations (4–5) should be used. Many researchers have followed this lead.

$$(4) \qquad X_t = \sum_{k=1}^{M_x} a_k X_{t-k} + \sum_{k=1}^{M_y} b_k Y_{t-k} + \epsilon_1$$

$$(5) \qquad Y_t = \sum_{k=1}^{M_x} c_k X_{t-k} + \sum_{k=1}^{M_y} d_k Y_{t-k} + \epsilon_2$$

This point is non-trivial if interest centers on whether the relationship is contemporaneous or occurs only through lags. If Y_t and its lags affect X_t, but only lags of Y_t are included, then the lags of Y_t will pick up the effect of the omitted Y_t and estimation will result in biased coefficients. Geweke (p. 1125) noted that the hypothesis of instantaneous causality has testable implications, and it makes no sense to maintain this hypothesis *a priori*. Therefore, the sensible procedure is first to test for instantaneous causality and, if it is not found, specify (4–5) for the Granger tests; otherwise specify (2–3). McCullough (1997) gives an example with stock market data where (4–5) show lagged causality, but when (2–3) are estimated only instantaneous causality is observed, and the lags become insignificant. The test for Y_t instantaneously causing X_t is equivalent to testing (4) as a restriction on (2). Due to the specification of the equations, only the existence of instantaneous causation can be inferred, not its direction (Geweke). Therefore, it is sufficient to test either (4) as a restriction on (2), or (5) as a restriction on (3), but not both.

Table 2. Lag-length Selections

	SOY	SST
AIC	16	17
SC	2	13
HQC	2	13

To implement Granger Causality tests, lag-lengths must be selected for the regressions, i.e., M_x, and M_y. We do so by appealing to various model selection criteria, specifically the Akaike Information Criterion (AIC), the Schwarz Criterion (SC), and the Hannan and Quinn Criterion (HQC):

$$(6) \qquad \text{AIC}(m, T) = \ln(\hat{\sigma}_m^2) + \frac{2m}{T}$$

$$(7) \qquad \text{SC}(m, T) = \ln(\hat{\sigma}_m^2) + \frac{m \ln T}{T}$$

$$(8) \qquad \text{HQC}(m, T) = \ln(\hat{\sigma}_m^2) + \frac{2m \ln(\ln T)}{T}$$

where $\hat{\sigma}_m^2$ is the maximum likelihood estimator of the error variance, m is the number of regressors. The length of an ENSO period is known to be 12 to 18 months (Trenberth and Hoar), so we choose 18 months as the maximum possible lag for both SOY and SST. Applying the various methods to each series produces the results in Table 2.

The AIC is well known to overfit even asymptotically, and the SC, while consistent, tends to underfit in finite samples. However, since the results of Granger Causality tests can be dependent on the specification of lag length, we run all our tests for a variety of

Table 3. Does SST Cause SOY? Marginal Significance Levels Granger Causality F Tests for Various Lags of SST and SOY

Lags of SOY	SST	msl	Lags of SOY	SST	msl	Lags of SOY	SST	msl
2	13	0.54	7	13	0.50	12	13	0.38
2	14	0.57	7	14	0.55	12	14	0.42
2	15	0.30	7	15	0.29	12	15	0.20
2	16	0.12	7	16	0.14	12	16	0.10
2	17	0.12	7	17	0.12	12	17	0.07
3	13	0.52	8	13	0.48	13	13	0.46
3	14	0.55	8	14	0.53	13	14	0.52
3	15	0.31	8	15	0.29	13	15	0.26
3	16	0.13	8	16	0.13	13	16	0.12
3	17	0.12	8	17	0.11	13	17	0.09
4	13	0.53	9	13	0.48	14	13	0.27
4	14	0.58	9	14	0.53	14	14	0.31
4	15	0.31	9	15	0.29	14	15	0.21
4	16	0.15	9	16	0.14	14	16	0.09
4	17	0.13	9	17	0.11	14	17	0.08
5	13	0.53	10	13	0.38	15	13	0.23
5	14	0.58	10	14	0.42	15	14	0.27
5	15	0.31	10	15	0.21	15	15	0.15
5	16	0.16	10	16	0.10	15	16	0.09
5	17	0.14	10	17	0.08	15	17	0.09
6	13	0.53	11	13	0.38	16	13	0.26
6	14	0.57	11	14	0.42	16	14	0.30
6	15	0.31	11	15	0.22	16	15	0.16
6	16	0.15	11	16	0.10	16	16	0.10
6	17	0.13	11	17	0.08	16	17	0.08

lag-lengths, and find that the qualitative results do not change. In particular, we run the regressions with 2 to 16 lags for SOY and 13 to 17 lags for SST (for a total of 75 regressions).

First, we tested for instantaneous causality. Letting SOY correspond to X and SST to Y in equation 2, this is simply a t-test on the null hypothesis that $b_0 = 0$. For all 75 regressions, in no case was there any evidence of instantaneous causality. Therefore, we proceeded to tests based on equation 4, where again SOY corresponds to X and SST to Y. Testing whether Y causes X amounts to an F-test of the null hypothesis that all the coefficients b_k in equation 4 equal zero. In the present case, we tested whether SST causes SOY, letting the lags of SST range from 13 to 17 and letting the lags of SOY range from 2 to 16. Results are presented in Table 3 which gives the marginal significance level of the F-test for each of the 75 regressions. In no case did we reject the null hypothesis that SST does not cause SOY. We are not troubled that there is not a single rejection of the null in all 75 tests. At the 1-percent level the probability of observing no rejections is $0.99^{75} \approx 0.47$. Also, running the tests in the other direction, we did not find that SOY causes SST.

An obvious problem is that the Granger tests require that all the lags be included in the regression, while there is substantial reason to believe only a few of the 16 (or 17 lags) are significant. The inclusion of unnecessary, irrelevant lagged variables may bias the tests toward non-causality. Therefore, we appealed to subset autoregression to restrict the parameterization of the lag representations of each series. When each series is represented by a constant and lags 1, 2, and 12, again it is found that SST does not Granger-cause SOY and conversely. As an additional attempt to find a 48-month signal, we also represented each series by a constant and lags 1, 2, 12, and 48. Again, we found no evidence of relationship. In sum, we find that SOY contains no predictive information for SST and SST contains no predictive information for SOY.

Conclusions

The emerging technology of seasonal climate forecasting has tremendous implications for agriculture (e.g., Mjelde *et al.*). The economic potential associated with climate forecasts in general, and with ENSO forecasts in particular, stems from their capability of improving crop mix and crop management decisions. That capability, already estimated to be $200 billion per year for the U.S. (Solow et al.), might be greater still if ENSO forecasts could be shown to have predictive value for crop prices as well. Because of its status as a major commodity whose price fluctuations have been less influenced by U.S. government intervention, soybean prices have been the focus of research investigating whether an ENSO/ price relationship might exist (Keppenne). ENSO could be expected to influence soybean prices either through its effects on weather conditions or indirectly through its effects on substitute commodities (e.g., other oil seeds, fish meal). Climatological research has found strong relationships between ENSO and weather parameters in the Gulf Coast, Northeast, Southwest, and Northwest regions of the United States (Ropelewski and Halpert 1986, 1987, 1989), although the relationship for the Midwest is less strong (Montroy, Richman and Lamb).

We have attempted to characterize the robustness of the ENSO/soybean price relationship originally found by Keppenne to alternative definitions of those variables and to determine whether that relationship has practical economic content. While we are able to corroborate Keppenne's finding of a relationship, the nature of the relationships are different: Keppenne finds a 48-month cycle that corresponds to the frequency of ENSO events, while we find a 12-month cycle. Additionally, when we test for causality we do not find any evidence for this more economically meaningful relationship. In sum, our findings support Keppenne's conclusion of a relationship between interannual climate and soybean prices, although we are not able to attribute the relationship to ENSO or to say that it is economically important.

Abbreviations Used

AC	autocorrelation
AIC	Akaike Information Criterion
ENSO	El Niño-Southern Oscillation
HQC	Hannan and Quinn Criterion
msl	marginal significance level of the *F*-test
PAC	partial autocorrelation
SC	Schwarz Criterion
SOI	Southern Oscillation Index
SOY	monthly soybean price received by farmers, USDA/NASS
SST	sea surface temperature anomaly index

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