Recent Developments in Unit Root Tests and Historical Crop Yields

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Selected Paper prepared for presentation at the Agricultural & Applied Economics Association's 2011 AAEA & NAREA Joint Annual Meeting, Pittsburgh, Pennsylvania, July 24-26, 2011.

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Abstract

This study conducts an investigation on the application of classical unit-root tests using parametric tests (the augmented Dickey-Fuller, 1979 – ADF), and nonparametric tests (Phillips and Perron, 1988—PP) to corn and soybean yields in the Delta states using county-level data from 1961 to 2009. The main concern of the paper is to assess what would be drawn about nonstationarity in crop yields using these tests versus using modified versions of these tests (Ng and Perron, 2001) that are assumed to solve size and power problems associated with the ADF and PP tests. The investigation focuses on methodological aspects of the classical tests, uncovers the nature of filtered yields often needed prior to density estimation, sheds light on the effect of lag truncation and provides guidance for future work. It is found that the complexity in yield behavior is such that at very small samples (40 observations or less), results can lead to ambiguous findings in larger samples (49 observations). This sample size analysis with county-level yield data uncovers that negative moving average effects are present and help explain certain ambiguous findings. As a by-product, this paper contains a condensed review of literature on unit-roots that may prove useful in applied research.

Key Words: Crop yields, nonstationarity, unit-roots, density estimation.

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The large but inconclusive literature on crop yield distributions has been recently summarized and empirically revisited by a number of researchers (e.g., Harri et al. ,2008) using a variety of yield models for several thousand data series at the county level for U.S. crops. One salient finding in these papers is the limited support for stochastic trends in yields. The main issue driving this type of research has to do with the appropriate specification of crop yield distributions which are essential in risk management in agriculture. Clearly, if crop yields were nicely behaved (independent, random, and normal), specifying the distribution function would be trivial and probability estimates would be easy to obtain. In practice, however, yields must be filtered (transformed) prior to identifying a distribution function, and the question of how to best do this remains an open one. When using historical crop yields, it is well documented that yields can behave as either deterministic (e.g., linear trend) or stochastic (e.g., unit-root). Harri et al., for example, find limited support for stochastic trends in yields..

The extensive literature on this subject has acknowledged the usefulness of the ADF and PP tests in determining the most adequate functional form to describe technological change in yield data. Also, the temporal dependence, heterogeneity, and the finite sample equivalence between a trend-stationary process and an ARIMA(0,1,1) with a negative MA coefficient close to the unit-circle has led some to argue that the standard PP test may be a better choice. Recent developments in unit-root tests solve the poor size and power performance of the standard ADF and PP tests and provide new modified tests. Although modifications to the standard ADF and PP tests have been published in the econometrics literature over the past decade, it is not until recently that modifications with improved size and power have been refined, and this may explain the slow adoption of these tests in applied research. The modification deals with important empirical omissions in the use of unit-root tests that should prove useful in a wide variety of applications. First, modifications to statistical selection criteria used in the identification of lag-length (e.g., using MAIC rather than AIC-- Ng and Perron, 2001; Perron and Qu, 2007) suggest that lag-length selection using standard criteria such as the AIC tends to be too small in the presence of moving average processes with large negative roots. Second, recent work has shown that the modified tests can have global power problems because of the dependence on the unit-root hypothesis; therefore, the estimation of the unit-root must be decoupled from that of the long run variance of the process for the tests to have good size properties when the long-run variance is estimated using an autoregressive spectral density estimator. These recent developments are relevant to risk analyses with crop yields because they accommodate frequently reported regularities in crop yields such as serial correlation, deterministic components, and non-Gaussian behavior. This paper applies these recent developments to county-level historical crop yields for corn and soybeans in the Mississippi River Delta Region (Texas, Louisiana, Mississippi, Arkansas, and Missouri) using county-crop yields with at least 20 observations to 2009 (a total of 302 counties). The impact on yield probability estimates from the application of existing procedures and the new methods are calculated.

Literature on Unit Roots

Dickey and Fuller (1979) and Said and Dickey (1984) are perhaps the two most influential papers on tests for unit roots (DF tests). Of interest is testing the null hypothesis that the coefficient on the one-period lagged term of the dependent variable being tested for unit-roots equals one versus the alternative that this coefficient is less than one (a stationary alternative hypothesis). These tests found wide applicability in economics research and are now standard tools in most econometrics software packages. Because the DF tests often require the estimation of an autoregression with one or more lags on the first-differences of the dependent variable, a statistical model selection criteria is used to determine the lag length; the DF test calculated from this autoregression is referred to as the Augmented Dickey-Fuller (ADF) test. Phillips and Perron (1988) developed a nonparametric alternative to the ADF tests (PP tests) that found similar wide applicability.

The ADF and PP tests can be specified under three basic models, which can be specified as:

$$(1)\ \Delta y_t = \alpha_0 + a_2 t + \gamma y_{t-1} + \sum_{i=1}^{m} \beta_i \Delta y_{t-i} + \varepsilon_t$$

$$(2)\ \Delta y_t = \alpha_0 + \gamma y_{t-1} + \sum_{i=1}^{m} \beta_i \Delta y_{t-i} + \varepsilon_t$$

This is a regression of first-differences in (Δy_t) on a constant term (α_0), a linear trend $(a_2 t)$, a lagged yields (γy_{t-1}) and lagged differences of yields. If there are no deterministic components in the series, then the first two terms are omitted generating a third model without a constant and without a trend. Some econometric packages (e.g., SHAZAM) report test statistics for those three models. While it is well known that a t-type statistic can be used to test for a unit-root, it appears less well known (or less often used) that Phillips (1987), and Phillips and Perron suggested a testing strategy for unit-roots that should first decipher whether the series in question is trend deterministic (e.g., represented by a simple linear trend) versus trend stochastic (e.g. unit-root). Such a test would require testing a joint hypothesis that the γ and α_2 parameters in equation (1) equal zero, and of course, this is a classical F-test. Phillips and Perron recommend using this test prior to proceeding with other tests.

While an extensive review of the literature on unit-roots for applied researchers may prove beneficial, we only provide a brief list of the works (in addition to the papers cited in the previous section) that reflect the main historical progression in testing for unit-roots. Schwert (1989) and Perron and Ng (1996) provided Monte Carlo evidence suggesting that when the moving-average polynomial of the first-differenced series has a large negative root, many tests have size problems, resulting in over-rejection of the unit-root hypothesis. Similarly, the low power of these tests in the presence of an autoregressive coefficient close to but less than one was noted early (e.g. DeJong et al., (1992)). Using a proposition in Stock (1990), Ng and Perron (1996) introduced a class of modified unit-root tests with better power (more robust to size distortions in the presence of negative serial correlation). Later on, Ng and Perron (2001) applied local GLS detrending (Dufour and King (1991); Elliot, Rothenberg, and Stock (1996)) to the modified tests to obtain gains in size and power when the modified tests are estimated using an autoregressive spectral density estimator at frequency zero. These findings also showed that appropriate selection of the truncation lag was crucial, an issue also studied by others (e.g. Ng and Perron (1995), and Lopez (1997)) who showed via simulation experiments that there is a strong association between the identified lag-length and the size and power of the tests. Ng and Perron (2001) introduced a modified AIC (referred to as MAIC) to resolve the lag-length truncation problem (Haldrup and Jasson (2006) provide an excellent survey of these developments). A few years later, Perron and Qu (2007) discovered that a simple modification to the lag-length truncation in Ng and Perron (2001) using OLS (rather than GLS detrending in selecting the MAIC truncation) would result in tests having an exact size. All these developments (and an R routine to estimate the tests) can be found in Lupi (2009).

Unit-roots in Crop Yields

Probability density estimation is a recurrent field of research in agricultural economics. It is of particular interest in risk assessment and has been applied to crop yields since the fifties. Foote and Bean (1951) followed by Day (1965) were the first to discuss the issue of non-normality in crop yield distributions. Their pioneer works laid the foundation to a vast statistical quest on the subject. Gallagher (1986 and 1987), for example, used a Gamma distribution to estimate corn and soybean yield density functions and found evidence of negative skewness, thus suggesting that yields are non-normally distributed. Nelson and Preckel (1989) opted for a beta distribution to estimate corn yield distributions conditional on fertilizer application. According to the authors, the beta distribution has the advantage of being flexible as it captures the three moments of a probability distribution. Taylor (1990) brought for the first time the use of the multivariate non-normal probability density function that can work under small samples. Taylor found both univariate and multivariate densities for corn, soybeans and wheat to be negatively skewed. Taylor's work was the motivation for other multivariate studies such as Ramirez (1997) who also reported negative skewness. Moss and Shonkwiler (1993) estimated an inverse hyperbolic sine transformation to model corn yields and found negative skewness. Goodwin and Ker (1998) were the first to apply non-parametric techniques to crop yield distributions. Ker and Goodwin (2000) reexamined Goodwin and Ker's (1998) methodology and found significant efficiency gains in estimating conditional yield densities via the empirical Bayes nonparametric kernel density estimator. In view of the diversity of distributions, Nelson (1990) attempted to show the impact of the distribution choice on probability estimates comparing normal and gamma distributions. Other authors have also tried to compare alternative distributions based on their performance such as Turvey and Zhao (1999), Norwood *et al.* (2004) and Sherrick *et al.* (2004). This list of works is far from exhaustive but illustrates the array of statistical interest in finding adequate specifications of yield densities.

The choice of the distribution is not the only matter of disagreement. Indeed, the presence of trends in crop yields, either deterministic (e.g., linear trend) or stochastic (e.g., unit-root), has been largely questioned. In the early literature, levels were used to estimate crop yield density functions. Foote and Bean (1951) were the first to notice the trending behavior of corn yields and that the data generation process (DGP) of the latter was most likely to be non-random. Likewise, Day (1965) insisted on the importance of understanding stochastic properties of crop yields in risk assessments. After WWII, with the technological changes that occurred in agriculture in the U.S. as well as in Europe, the upward trend in crop yields became unquestionable. Therefore, researchers started to model this behavior by fitting a linear trend to crop yield data prior to density estimation (e.g., Gallagher, 1986 and 1987 and Turvey and Zhao, 1999). Researchers rapidly realized that the impact of technology as well as major severe climatic events was not so easy to model. Overcoming these drawbacks, Zapata and Rambaldi (1989) and then, Kaylen and Koroma (1991) considered stochastic trends in crop yield density estimation for the first time. Similar works are those of Moss and Shonkwiler (1993) who allowed stochastic trends in crop yield series using nested models. Goodwin and Ker (1998) carefully determined the DGP and found that an ARIMA (0,1,2) and thus stochastic processes, best represented crop yield series. In consequence, they have applied first differencing to the data before generating non-parametric (Kernel) crop yield density functions. The use of ARIMA filters in crop yield distribution estimation is rooted in some traditional works (e.g. Bessler, 1980, p.666). As suggested by time-series theory and simulated in Zapata and Rambaldi (1989), arbitrary transformations can generate series with different properties than those of the underlying DGP process, thus leading to misspecified probability density functions and biased probability estimates. In this spirit, Atwood, Shaik and Watts (2003) have assessed through a Monte Carlo experiment the effect of alternative detrending methods on normality tests. Although they shed light on the consequences of using an incorrect filter, their work was limited to deterministic processes. As in Zapata and Rambaldi (1989), Sherrick *et al.* (2004) determined the DGP of crop yields using unit-root tests. Recently, Harri et al. (2008) summarized the literature on crop yield distribution using a variety of yield models for several thousand data series at the county level for U.S. corn, cotton, soybean, and wheat. Using standard unit-root tests (Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP)) they found little evidence for stochastic trends. But, Maradiaga (2010), using ADF tests, concluded that about 74% of crop yield series in Arkansas and

Louisiana were characterized by stochastic processes. One consensus in this rich literature in stochastic trends in yields is a "lack of consensus" on how to best describe the time series properties of historical yields.

Methods

In an effort to complement previous work in this field, we provide a strong emphasis on current practice by applying the ADF and PP tests as commonly reported in the literature (e.g., Harri et al., 2008). This typically involves the estimation of the ADF and PP tests to yield data in a model with a constant (equation (2)) and a constant and trend (equation (1)). To determine the lag truncation of each test, a statistical selection criteria (the AIC) is used. Once these preliminary results are obtained, we divide the findings for yields in two types of trends: a) stochastic trends (implying the possibility of unit-roots in yields), and b) deterministic trends (implying that a linear trend may be an appropriate yield filter). Then side-by-side comparisons of the ADF and PP tests relative to the modified tests (DFGLS and MPP- Ng and Perron, 2001) are estimated. In theory, the modified versions of these should be more powerful and have better size than the classical ADF and PP tests. The standard tests are specified once an optimal lag length in the augmented regressions has been identified using the modified AIC criterion (MAIC). Frequency histograms were obtained by comparing residuals from ARIMA(0,0,1) on linearly detrended yields and an ARIMA(0,1,1,) model, and tests comparing two-sample empirical CDFs (empirical CFDs from ARIMA(0,1,2) vs. polynomial detrending).

Data

Historical corn and soybean yields (bu/acre) for Arkansas, Louisiana, Mississippi, Missouri and Texas were obtained from the National Agricultural Statistics Service (http://www.nass.usda.gov/) for the 1961-2009 period. The data are aggregated county level yields for irrigated and non-irrigated crops. Four sample sizes were used with a production history of 20 (1990-2009), 30 (1980-2009), 40 (1970-2009), and 49 (1961-2009) years with no missing observations. These data screening resulted in a total of 315, 302, 298, and 254 counties (samples) at the 20, 30, 40, and 49 sample sizes, respectively.

Descriptive Analysis of Corn Yields

Descriptive statistics for historical (1990-2009) corn and soybean yields in Arkansas, Louisiana, Mississippi, Missouri and Texas are shown in Table 1. The five states county average for corn yields was 114.17 bu/acre. County level corn yields were highest at 185 bu/acre in Atchison, Missouri in 2009 and lowest at 16.7 bu/acre in Fayette, Texas in 1996. The highest standard deviation for county corn yields was 52.49 in bu/acre in Texas, while the lowest was 23.39 bu/acre in Mississippi. In the case of soybeans, the five states county average yield was 30.05 bu/acre. County level corn yields were highest at 54.5 bu/acre in Atchison, Missouri in 2009 and lowest at 11 bu/acre in Fannin, Texas in 2006. The highest standard deviation for county corn yields was 7.66 in bu/acre in Mississippi, while the lowest was 5.8 bu/acre in Arkansas.

Table 1. Descriptive Statistics for Corn and Soybean Yields for the Mississippi Delta States.

Crop	State	Mean	Maximum	Minimum	Std Dev
Corn	Arkansas	133.17	184	70.2	24.43
	Louisiana	125.02	180.3	57.5	24.37
	Mississippi	105.23	182.2	51.1	23.39
	Missouri	116.89	185	36.8	27.5
	Texas	109.55	235	16.7	52.49
Soybeans	Arkansas	31.52	46	17	5.8
	Louisiana	30.41	51.9	11.2	7.59
	Mississippi	28.7	50	10.2	7.66
	Missouri	34.8	54.5	13.1	6.95
	Texas	26.3	49	11	7.32

Classical ADF/PP Unit-Root Results

Three hypothesis were tested (a) a joint test is carried to test for the significance of the trend and the presence of a unit-root $[Ho: a_2 = \gamma = 0]$ in equation (1), (b) a t- test for the significance of the unit-root $[Ho: \gamma = 0]$ in equation (1), and (c) a t-test of the significance of the unit-root carried$[Ho: \gamma = 0]$ in equation (2). The results are shown in Table 2 and are organized by total samples (the section labeled Total) with three horizontal blocks and by crop (the section labeled By Crop) with two horizontal blocks. As pointed out earlier, the joint test is used to determine whether yields are stochastic or trend deterministic. If the joint test rejects Ho, the conclusion is that the unit-root and no-linear trend are jointly rejected, leading to the decision that yields are trend deterministic. If trend deterministic behavior is found, there is no need for further testing for unit-roots; but if stochastic trends are found, an additional test (a t-test) should be estimated to decide whether unit-roots are present. Two of these t-statistics are shown in Table 2: the t-statistics for unit-root in a model with a constant and a linear trend (the second horizontal block in the section labeled Total—this is test (b) above), and the t-statistic for unit-root in a model with a constant only (the third horizontal block in the section labeled Total—this is test (c) above). The salient finding from the total section of Table 2 is that at any sample size, the ADF test

Table 2. Augmented Dickey Fuller and Phillips-Perron Tests Results (Failing to Reject).

Test/Ho		ADF				PP			
	Sample Size	**20**	**30**	**40**	**49**	**20**	**30**	**40**	**49**
Total									
Trend:	**Proportion**	**75.24**	56.29	55.70	73.62	**13.65**	0.99	0.67	0.39
$\alpha_2 = \gamma = 0$	**Count**	**237**	170	166	187	**43**	3	2	1
(F-Test)	**# of samples**	**315**	302	298	254	**315**	302	298	254
Trend:	**Proportion**	97.89	91.76	97.59	92.51	95.35	66.67	50.00	0.00
$\gamma = 0$	**Count**	232	156	162	173	41	2	1	0
(T-Test)	**# of samples**	237	170	166	187	43	3	2	1
Constant:	**Proportion**	85.34	94.87	98.15	96.53	75.61	50.00	100.00	0
$\gamma = 0$	**Count**	198	148	159	167	31	1	1	0
(T-Test)	**# of samples**	232	156	162	173	41	2	1	0
By Crop									
Corn									
Trend:	**Proportion**	76.92	45.14	45.77	77.36	5.13	0.69	0.70	0.94
$\alpha_2 = \gamma = 0$	**Count**	120	65	65	82	8	1	1	1
(F-Test)	**# of samples**	156	144	142	106	156	144	142	106
Soybeans									
Trend:	**Proportion**	73.58	66.46	64.74	70.95	22.01	1.27	0.64	0.00
$\alpha_2 = \gamma = 0$	**Count**	117	105	101	105	35	2	1	0
(F-Test)	**# of samples**	159	158	156	148	159	158	156	148

identifies stochastic trends. For example, at 20 observations, 75.24% of crop yields (237 counties) could be assumed to have a stochastic trend (these cells are highlighted in bold). In striking contrast, the PP test suggests that only a small percentage of the samples have a stochastic trend. For example, at 20 observations, only 13.65% of crop yields (43 counties) could be assumed to have a stochastic trend.

The third horizontal block of Table 2 shows the t-statistic for test (b). Concentrating on the 237 trend stochastic crop yields based on the ADF results, it is found that that most of these have a unit root. For example, at 20 observations, the ADF indicates that 97.89% (232 counties) have a unit-root in a model with a constant and a trend and about 85.34% (198 counties) have unit-roots when testing with a model that has a constant but no linear trend. This is a non-trivial finding! If a trend is present but a model with a constant only is used in testing for unit-roots with ADF, the differential (97.89% - 85.34% = 12.55%) represents the percent of missed unit-roots.

Finding reasonable explanations for the disparity of results is not simple but perhaps can be explored by recurring to well-known theoretical results. Figure 1 presents a histogram of the moving average coefficients that resulted from fitting an ARIMA (0,0,1) model to residuals from linearly detrended corn and soybean yields (all samples). After detrending crop yields it is clear that yields were successfully converted to stationary processes in about 87, 91, 98 and 100 percent for 20, 30, 40 and 49 samples sizes, respectively. The counterparts are the MA coefficients close to -1 indicating the presence of a stochastic trend. That these effects are present is cause for thinking that Ng and Perron (2001) and Perron and Qu (2007) modified tests would be a better method (better size and power of the tests) to get closer to the time-series properties of crop yields.

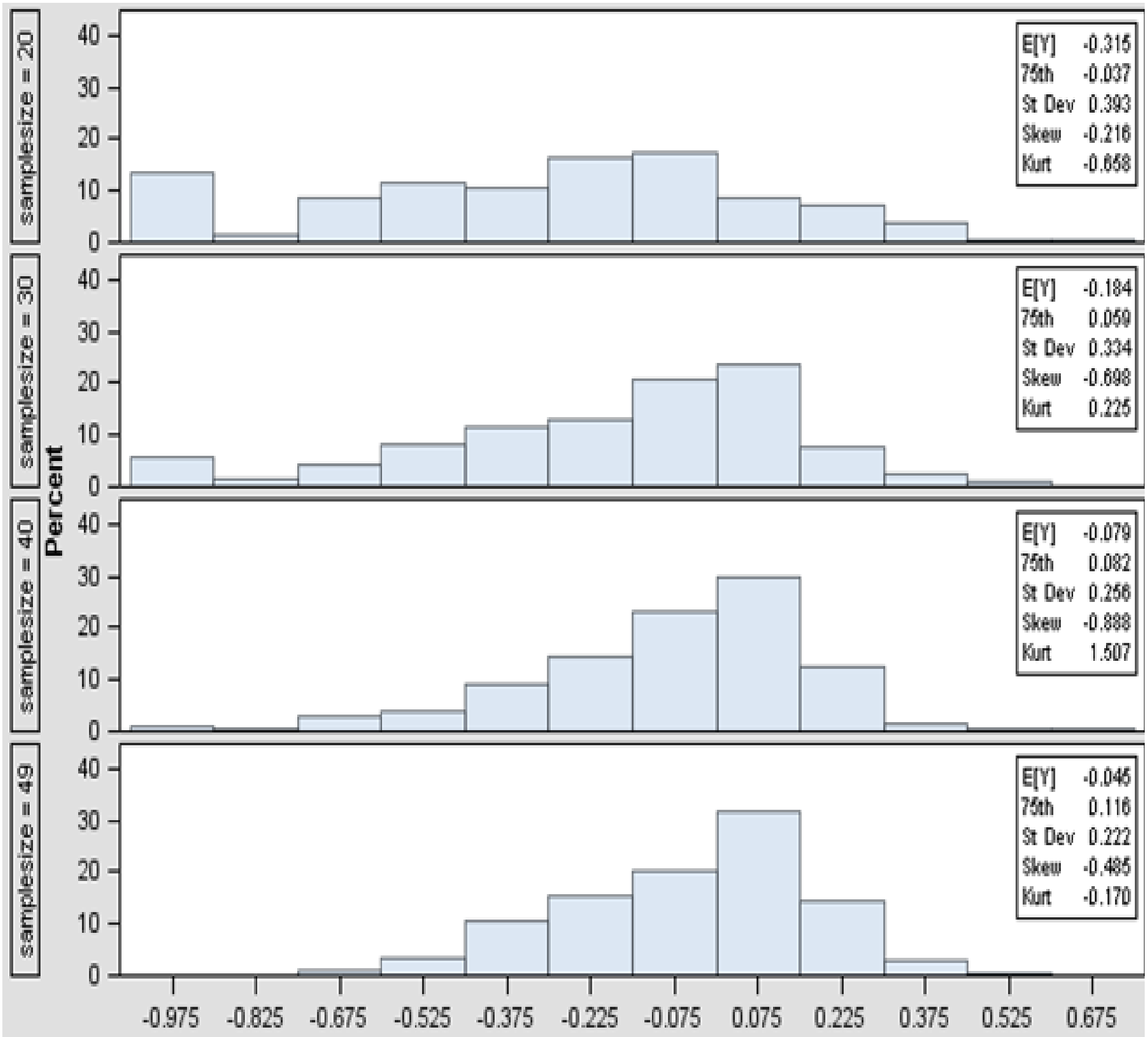

Figure 1. Moving Average Coefficients from Fitting an ARIMA (0,0,1) to Detrended Crop Yields.

Figures 2 presents a histogram of the moving average coefficients that resulted from fitting an ARIMA (0,1,1) to corn and soybean yields (all samples). When first-differencing crop yield data, the remaining MA coefficients equal or very close to -1 (-0.9 to -1) were about 20, 6, 4, 4 percent for 20, 30, 40 and 49 sample sizes, respectively.

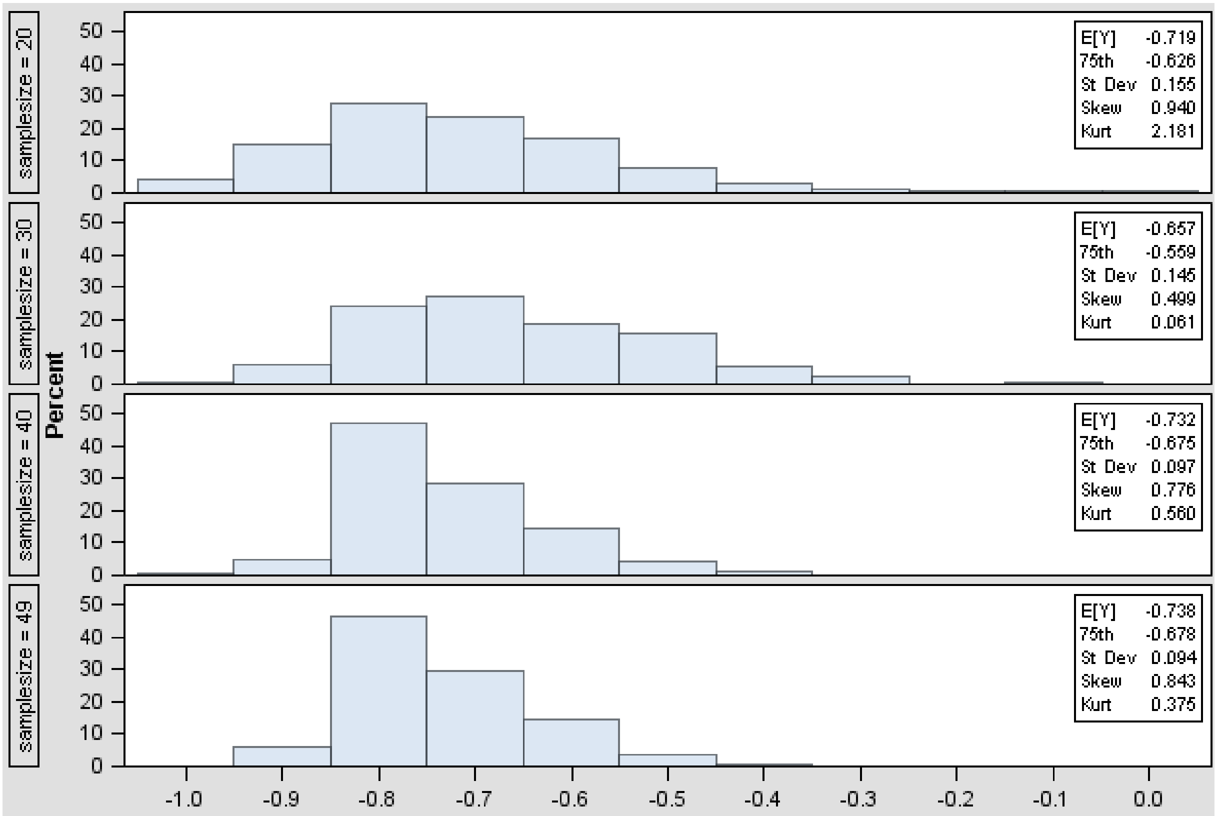

Figure 2. Moving Average Coefficients from Fitting an ARIMA (0,1,1) to Crop Yields (levels).

Modified DF/PP Unit-Root Tests

There are four tests for unit-roots that were re-estimated based on the modifications suggested in Ng and Perron (2001); these tests were “t-type” tests for unit-roots and included the ADF and PP tests of the previous section, and the DFGLS and modified Phillips-Perron (MPP). All four tests were estimated using the MAIC selection criterion of Ng and Perron (2001), so the lag length for the ADF and PP does not necessarily correspond to the lag-length used in the previous section. The results are shown in Figures 3-11. The top row in each of these figures contains histograms of the values of the t-statistics for unit-root from each of the tests (ADF-t, PP-t, DFGLS-t, and MPP-t). The t-test calculated from a model with a constant is labeled as (C) and from a model with a constant and a trend is labeled (C,T). Thus, ADF-t(C) is the histogram of the t-test values from 156 samples (see the label on the x-axis of the third block in each figure). The middle row in each figure corresponds to a histogram of the p-values for the test statistic above it (in row 1). The third row is the rejection rates: the bar on the left is the proportion of I(0) series and the one on the right is the proportion of I(1) series. We found that first, ADF, PP and DFGLS tests tend to give similar results which are generally the opposite of those in the MPP tests. In particular, using the three first tests leads to the conclusion that most crop yield series do not contain a unit-root. Second, as the sample size increases from 20 to 49 observations, the results of the MPP tests tend to converge to those of other tests. The convergence of the results of the four tests is especially true when a trend and a constant are included in the model. Third, the P-Values of the MPP tests are always higher than those of the other tests. Fourth, as expected, the results of the PP tests using the model with a trend and constant are globally consistent with the results suggested by the joint PP F-test.

In a model with a constant but no trend (labeled (C) in the figures), the t-test for unit-roots in corn yields (ADF, PP and DFGLS tests) generate similar findings (Figure 3, bottom portion-first three graphs): about the same rejection rates and the tests suggest that most series are I(0). Although the results are not reported here for samples at 30 and 40 observations, when the sample size increases from 20 to 49 observations, the DFGLS finds a higher percentage of I(1) series in a model with a constant (Figures 3 and 8). Also note that as the sample size increases, these three tests identify more unit-roots. When using the modified PP test, for a given sample size, the I(0)/I(1) ratio changes drastically relative to the other three tests - ADF, PP and DFGLS (Figures 3 and 8). In fact, with the modified PP a higher percentage of I(1) processes is found; this result holds for all samples.

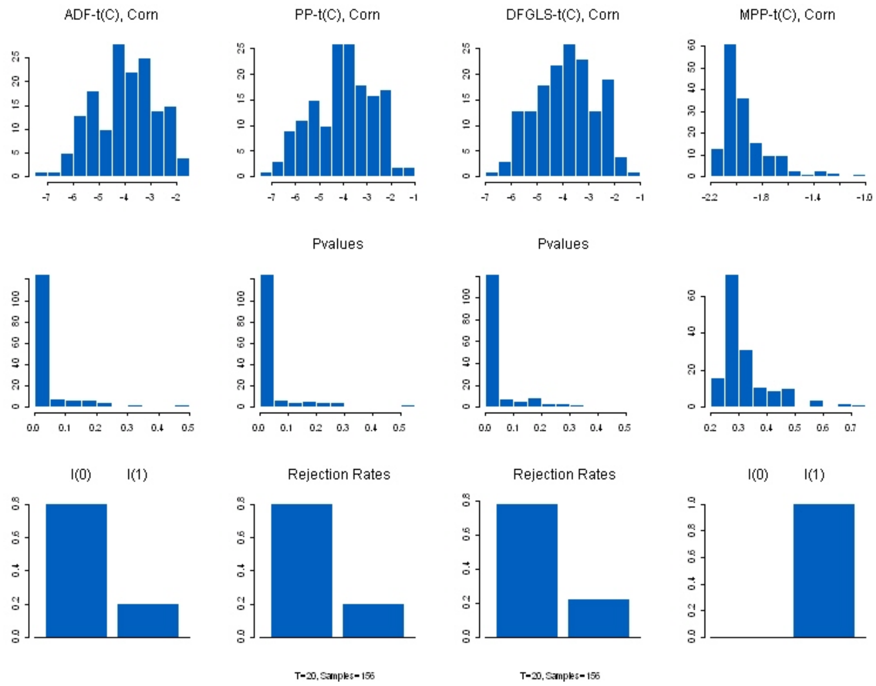

Figure 3. Unit Root Tests (t-statistics), Delta states, **Constant**, Corn, T=20.

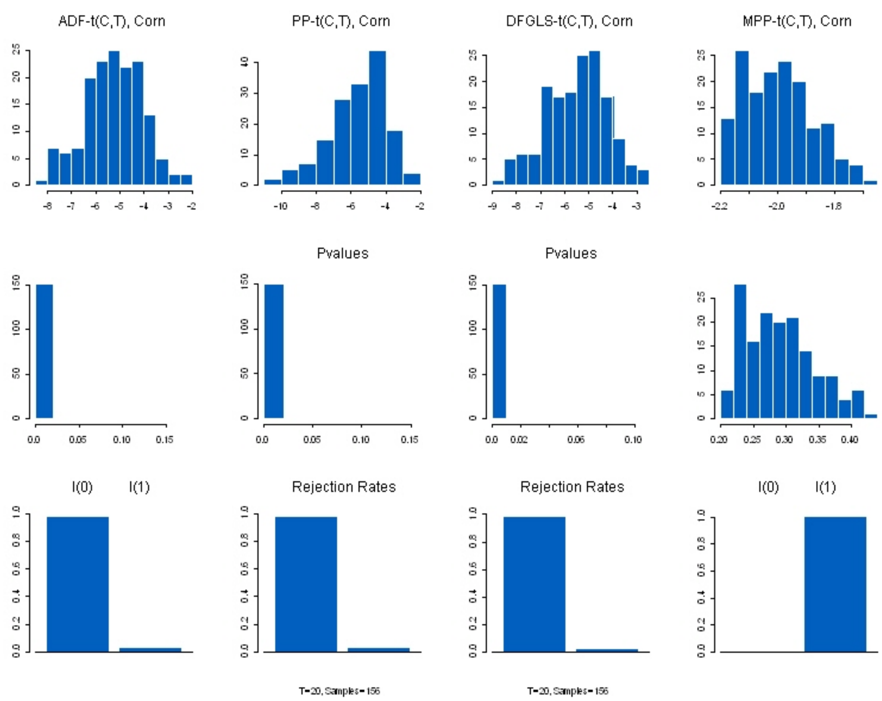

Figure 4. Unit Root Tests (t-stat), Delta states, Corn, **Constant and Trend**, T=20.

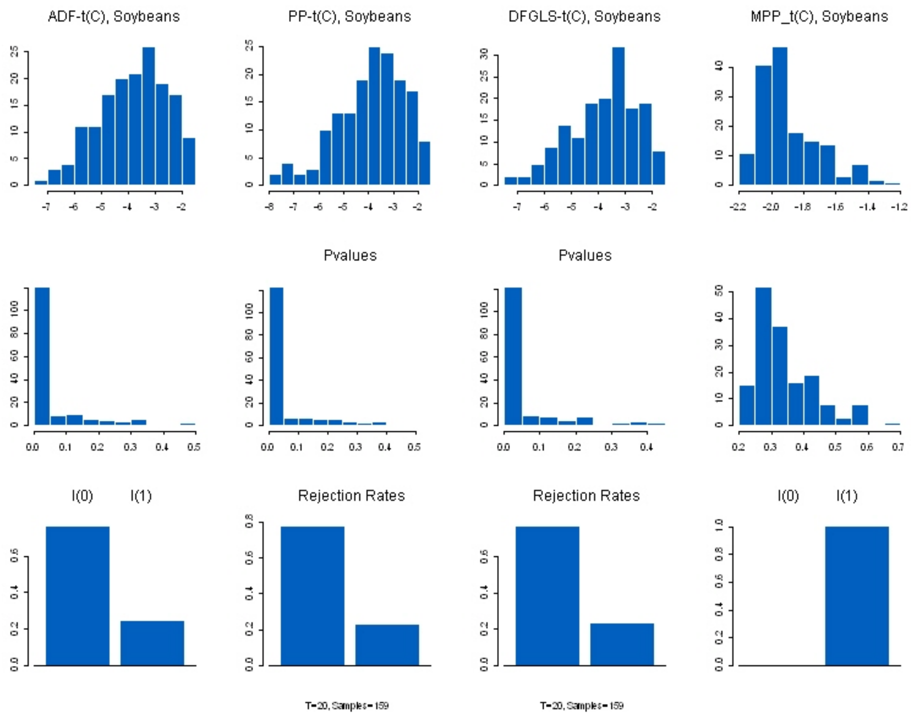

Figure 5. Unit Root Tests (t-statistics), Delta states, **Constant**, Soybeans, T=20.

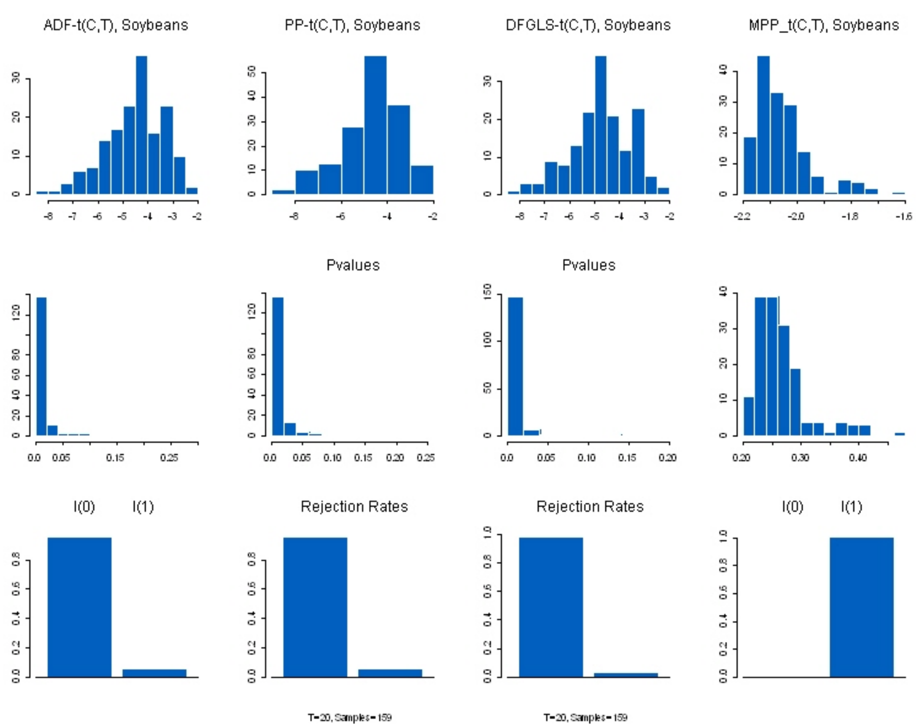

Figure 6. Unit Root Tests (t-statistics), Delta states, **Constant and Trend**, Soybeans, T=20.

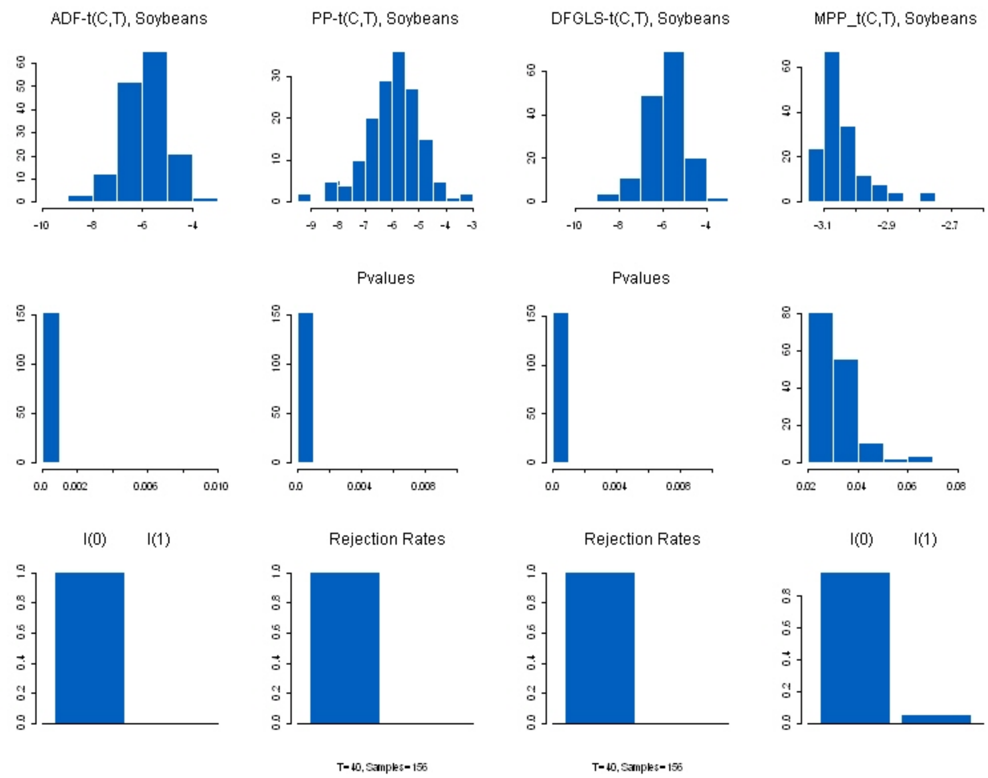

Figure 7. Unit Root Tests (t-statistics), Delta states, **Constant and Trend**, Soybeans, T=40.

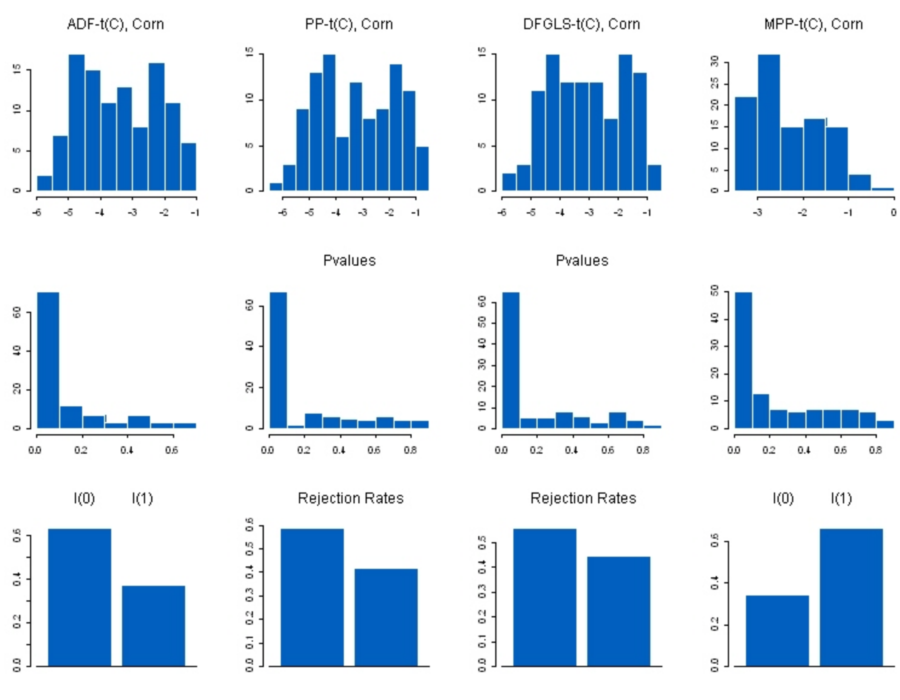

Figure 8. Unit Root Tests (t-statistics), Delta states, **Constant**, Corn, T=49.

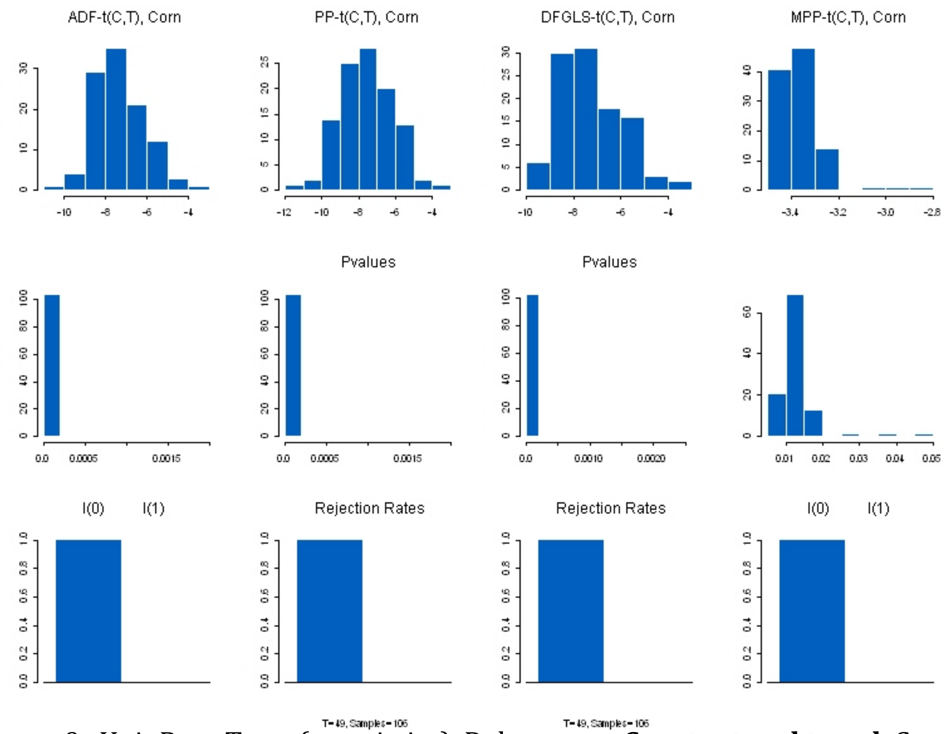

Figure 9. Unit Root Tests (t-statistics), Delta states, **Constant and trend**, Corn, T=49.

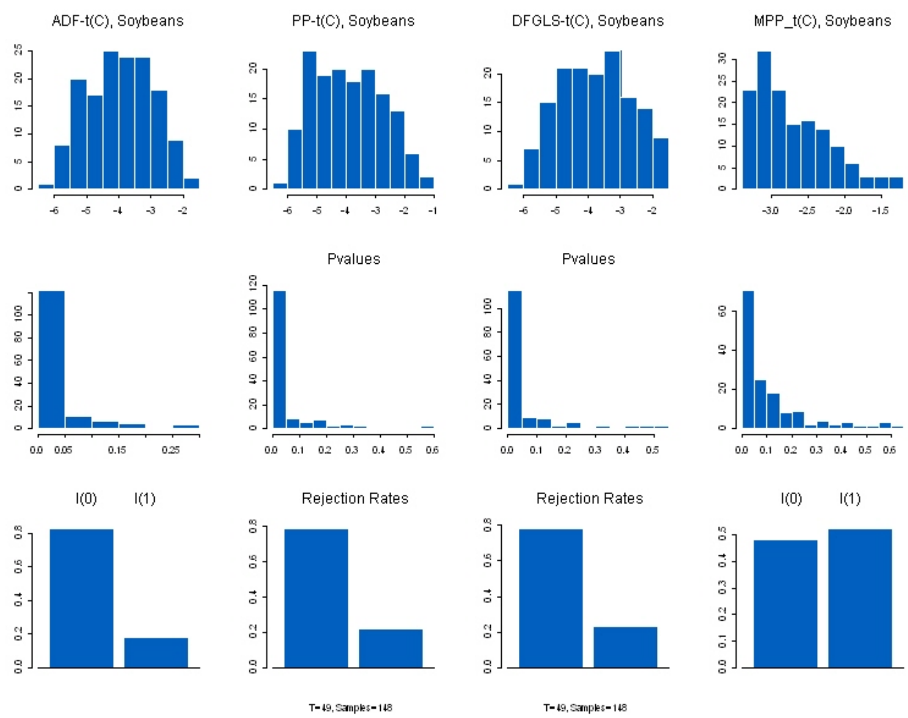

Figure 10. Unit Root Tests (t-statistics), Delta states, **Constant**, Soybeans, T=49.

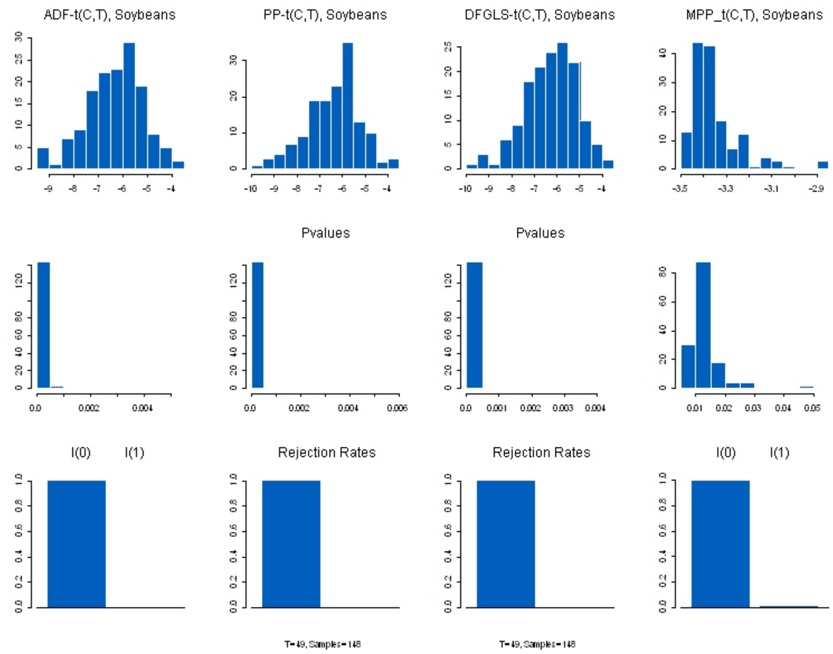

Figure 11. Unit Root Tests (t-statistics), Delta states, **Constant**, Corn, T=49.

When using the latter (MPP), as the sample size increases the percentage of I(0) processes tends to increase (Figures 3 and 8). Note also that the P-value is generally higher for the MPP test (Figures 3-12, middle block). Lastly, we found that the results from the ADF and PP tests are not consistent with the results obtained with the ADF joint F-test which found that about 23% (up to 55% depending on the sample size) of the samples were found to be trend deterministic or with the Phillips-Perron F-test where more than 95% of the series are trend deterministic at all sample sizes (Table 2).

In a model that includes a constant and a trend (labeled (C,T)) the main highlights for corn yields are that for a given sample size, most of the series are identified as I(0) when using either ADF, PP or DFGLS tests. These results hold as the sample size increases. Second, the MPP test gives similar results as in the ADF, PP and DFGLS tests at sample sizes T= 40 and 49 (Figure 9, results for T=40 not shown). However, at T= 20 & 30, the MPP test gives opposite results to the ones of ADF, PP and DFGLS tests (i.e. most are I(1) –Figure 4; results not shown for T=30). As before, the P-values are higher for the MPP tests (Figure 4 and 9). Note also that the results of the PPs test are consistent with the results of the joint test in Table 2.

For soybean yields in a model with a **constant only (labeled (C))**, we found that for all sample sizes, ADF, PP and DFGLS tests give similar results (i.e., most processes are identified as I(0) --Figures 5 and 10). On the contrary, a higher percentage of I(1) yields has been found when employing the MPP test (Figure 5). However, as the sample size increases, so does the relative percentage of I(0) yields and almost equals the percentage of I(1) – Figure 10).

Continuing with soybean yields, in a **model with a constant and a trend (labeled (C,T))**, for all samples, ADF, PP and DFGLS tests results are again similar; a majority of I(0) processes has been found (Figures 6, 7 & 11). On the contrary, employing the MPP test leads to a higher percentage of I(1) processes (Figure 6). However, as the sample size increases, from T=20 to T=40, the relative percentage of I(0) increases (Figure 6 & 7). As T increases to 49 observations, the results of the MPP test become similar to those of the other tests (i.e., 100% of the processes are found to be I(0) --Figure 11). Again, the results obtained when the PP tests are employed are consistent to that of the joint F-test (Table 2).

Discussion

A point that deserves discussion is that at small sample sizes, a large majority of I(1) processes are found when the MPP tests are employed. As the sample size increases, the results of the four tests converge (i.e. most processes are I(0)). A question that instantaneously comes to mind is why the results of the MPP tests are so drastically different from those of the other tests at small sample sizes? Is it because this particular test is performing better at small sample sizes or on the contrary, worse? Is this performance linked to the DGP of the series rather than directly to the sample size? A first element of response is that our results may support the statement of Ng and Perron (2001) that "the majority of tests suffer from severe size distortions when the moving-average polynomial of the first differenced series has a large negative autoregressive negative root" (Ng and Perron, 2001, p.1519). In fact, this statement also holds for detrended series. The general idea is that the performance of unit-root tests is poor when the error process presents strongly negative MA terms (Enders, 2010). "The consequence is over-rejections of the unit-root hypothesis" (Ng and Perron, 2001, p.1519). As a matter of fact, we found that when first-differencing or detrending crop yield data, the proportion of MA coefficients close to or equal to -1 was higher for small sample sizes (T= 20 and 30) (Figures 1 & 2).

Thus, we conclude that this may indicate that the ADF, PP and DFGLS tests were not able to identify the presence of unit-roots in crop yield series at small sample sizes (i.e. when more filtered series present a MA coefficient close to one). This explains the high proportion of I(0) found with these tests compared to the results of the MPP tests. This conclusion deserves an assessment through a Monte Carlo experiment, similar to Ng and

Perron (2001) but with smaller sample sizes in a yield-data coherent framework. Note that the smallest size that the authors used was 150 observations. Also of interest would be a closer examination of the performance of the DFGLS-t statistic in relation to a constant versus a constant and a trend model specification. The findings here are preliminary but lead to reasonable results in the first model but not the second.

We believe that the DGP should not be disconnected to what is happening in the field. Hence, it would be also interesting to link the abundance of series with strongly negative MA terms to the technological changes or climatic events that occurred in corn and soybean productions in Southern U.S. Recalling that the counties with small sample sizes correspond to crop yield observations that start in the early nineties and end today while for counties with large sample sizes we had observations since the early sixties. Recalling also that "the presence of the negative MA term means that ε_t has a one-unit effect on y_t in period t only" (Enders, 2010, p.220), a MA coefficient that is close to -1 may correspond to a negative shock whose effects are carried to the next crop season. Hence, we may hypothesize that severe climatic events may have occurred more frequently during the two last decades.

The search for improved methods to test nonstationarity of yield distributions is likely to continue. This paper has identified at least one area of future research that may prove useful in making more definite progress in the identification of yield distributions. Perhaps future research should also emphasize deeper thinking into the evolving nature of historical yields and how these can be best related to the theory of nonstochastic processes. We conducted an exhaustive evaluation testing the paired difference between empirical

CDFs generated from an ARIMA(0,1,2) and polynomially detrended yields to address the question of whether such differences are substantially large to significantly impact risk estimation. The results found no support for a significant difference between pairs of empirical CDFs, an issue that deserves closer investigation. Hamilton (1994) suggested to think in terms of "parsimonious DGPs" and not necessarily about the I(0) or I(1) nature of the data. Perhaps future studies of nonstationary yields will shed more light on this thinking.

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