A Century of Crop Yield Density Estimation with Perspectives

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A Century of Crop Yield Density Estimation with Perspectives

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Introduction

Day stated that "until a science of yield probabilities can be developed, correct decisions in agriculture are virtually impossible" (*JFE*, 1965).

Two popular filtering techniques used in crop yield density estimation (CDF) have been detrending and ARIMA, and CDF techniques have progressed from parametric to nonparametric (*e.g.*, Botts and Boles, *JFE*,1958; Gallagher, *NCJAE*,1986,1987; Goodwin and Ker, *AJAE*,1998; Norwood *et al.*, *AJAE*, 2004).

How do filters impact: empirical CDFs? Risk premium estimation? Crop insurance participation by farmers? and risk management at large? Some Monte Carlo evidence on detrending with small samples has been documented at the farm level (*e.g.*, Atwood et al. *AJAE*, 2003). How does filtering impact Empirical CDFs in aggregated time series for crop yields? More explicitly, are two ECDFs for the same data but from different filters statistically different? What are the implications for yield risk management?

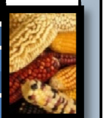
Objectives

1. To identify the stochastic Properties of corn and soybeans yields in Arkansas and Louisiana.
2. To determine the impact of alternative filters on corn and soybeans yield ECDF and probability estimates.
3. To asses the impact of alternative filters on ECDF with small samples.

Data

Table 1. Data and Counties

Crop/State	Arkansas	Louisiana
Corn	31	25
Soybeans	31	34
Source: NASS	> 30 Obs.	1960-2008

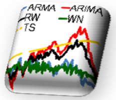


Methodology

Crop Yield Data Generating Processes (DGP)

1. Stationary (ST), $Y_t = a_0 + e_t$
2. Random Walk (RW), $Y_t = a_0 + Y_{t-1} + e_t$
3. Trend Stationary (TS), $Y_t = a_0 + a_2 t + e_t$

The DGPs are identified through unit root tests (*e.g.,* Augmented Dickey-Fuller test, 1979). The ECDFs are tested via a Kolmogorov-Smirnov test.



The Monte Carlo Experiment

Each DGP has four sample sizes: 25, 50, 100 and 200. Each sample was replicated 1000 times. Because the DGP can be sensitive to starting values we eliminated the 75 first observations from each process. Pre-testing with 10% of the total replications suggests that this approach generates samples from the true process with 5% reliability. DGPs are presented in table 2. Errors were drawn from the standard normal distribution N(0,1) – see Phillips, *Econometrica,* 1987.

Table 2. Parameter Values

DGP	Drift	Linear Trend		Lag (y)
	a0	a2		a1
WN	0	0		0
TS LT	2	0.8		0
RW	0	0		1
RWD	0.2	0		1
RWDT	0.2	0.001		1
	AR		MA	
	#	Coefficient	#	Coefficient
ARMA	1	0.7	1	0.5
ARIMA	1	1	1	0.5

Results and Discussion

Figure 1. Geographic Distribution of DGP

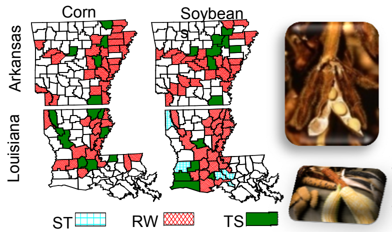


Figure 2. Results on Filtering

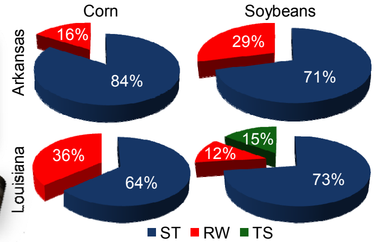


Figure 3. Effect of Filtering on Crop Yield Distributions

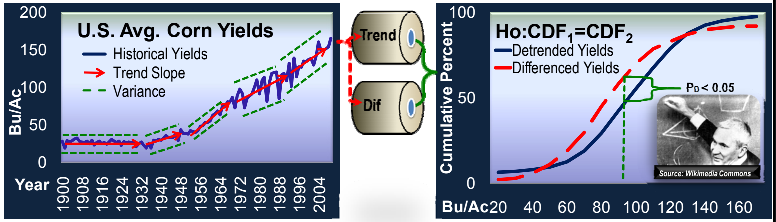


Table 3. Kolmogorov-Smirnov Test Results

			Rejection Percentages (%) under Ho							
			25 Obs		50 Obs		100 Obs		200 Obs	
Processes	Filters		α=0.05	α=0.1	α=0.05	α=0.1	α=0.05	α=0.1	α=0.05	α=0.1
WN	*Levels*	Differencing	0.60	1.20	1.00	6.50	5.70	13.30	30.40	52.60
WN	*Levels*	Detrending	0.70	1.70	0.00	0.40	0.20	1.10	0.20	0.40
TS	*Detrending*	Differencing	44.00	66.70	99.20	99.80	100.00	100.00	100.00	100.00
RW	*Differencing*	Detrending	2.30	6.50	26.40	34.50	85.10	91.40	100.00	100.00
RWD	*Differencing*	Detrending	3.70	9.40	32.30	44.40	89.70	95.20	100.00	100.00
RWDT	*Differencing*	Detrending	6.60	15.20	78.70	88.70	96.00	98.40	100.00	100.00
ARMA	*Levels*	Differencing	38.00	47.70	47.60	56.80	69.70	80.90	92.70	97.40
ARMA	*Levels*	Detrending	27.40	36.40	24.40	31.30	21.50	28.30	27.20	19.00
ARIMA	*Differencing*	Detrending	7.80	18.50	52.70	65.20	97.20	99.20	100.00	100.00

Main Results

Empirical

In Arkansas and Louisiana most crop yields have stochastic trends (RW); however, some are trend stationary (TS) or stationary in levels (ST).

Monte Carlo Simulation

1. Two sample ECDF K-S test rejects (Ho) equal distribution between two alternative filters.
2. Rejection rates increase fast with sample size and equal to 100% at 200 obs.
3. Detrending I(0) or I(I) series can lead to wrong ECDF and is worst in I(I) series.

Conclusions

1. The Distribution of percent errors is often skewed (positively or negatively) from zero ⇒ costly to sellers and buyers of crop insurance contracts.
2. Using a filter as a generalized model for corn and soybeans yield density estimation often leads to unreliable insurance premium rates.

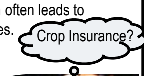


Figure 5. Percent Errors Distribution