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Improving Accuracy of Technological Trend Estimations In Farm Yield Models by Taking Weather Effects Into Account

Conradt, S.¹, Bokusheva R.¹, Finger R.² and Kussaiynov, T.³

¹ ETH Zurich, Agri-Food and Agri-Environmental Economics Group, Zurich, Switzerland.

² Wageningen University, Agricultural Economics and Rural Policy Group. Wageningen, the Netherlands

³ Kazakh Agrotechnical S. Seifullin University, Department of Economics, Astana, Kazakhstan

conradts@ethz.ch

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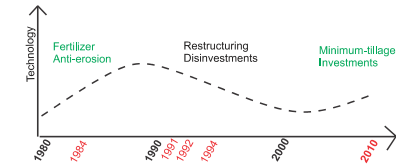
BACKGROUND

- The development of risk management instruments often requires historical data. Historical yield data however are subject to technological changes which have influenced yield level over time. Thus, prior to further analysis, historical yield has to be adjusted for technological trend, i.e. detrended. In some cases however, the estimation of a technological trend is complicated through a joint occurrence of three phenomena: High yield variations as a consequence of the exposure of rain-fed agriculture to extreme weather events, a high heterogeneity among the different farms in a region and a non-linear development of technological change. This situation is particularly relevant for transition and developing countries, where farming is more often exposed to extreme weather events and is mostly rain-fed [1].

- We investigate the technological trend estimation of these non-homogeneous, volatile yield data from Kazakhstan. More specifically we analyse

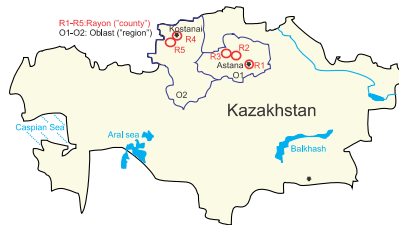
- the possibility of data aggregation,
- the applicability of robust regression techniques,
- the use of weather information in yield data detrending.

- As general tendency, we assume that the technological development followed a cubic trend from 1980-2011 [2].

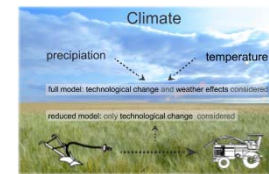


DATA & METHODS

- Wheat production data (1980-2011) from Kazakhstan (farm yield data (47), county (5), regional (2) and national data)
- Weather data (1980-2011) provided by the Hydro-Meteorological Agency of Kazakhstan



- Used detrending techniques: Ordinary Least Squares (OLS) and MM robust estimator [3]
- Tested for a trend up to a 3rd polynomial degree
- Included weather indices in the detrending model (full model): Selyaninov Index (HTC = 10 ΣPrecip / ΣTemp) [4] and cumulative precipitation (CP= ΣPrecip)
- Model selection with F-test (AIC criterion)



Reduced form model

$$y_i = \beta_0$$

$$y_i = \beta_0 + \beta_1 t$$

$$y_i = \beta_0 + \beta_1 t + \beta_2 t^2$$

$$y_i = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 t^3$$

Best model determined using F-tests

Full model

$$y_{ij} = \alpha_i \text{weather}_{c_j} + \beta_0$$

$$y_{ij} = \alpha_i \text{weather}_{c_j} + \beta_0 + \beta_1 t_j$$

$$y_{ij} = \alpha_i \text{weather}_{c_j} + \beta_0 + \beta_1 t_j + \beta_2 t_j^2$$

$$y_{ij} = \alpha_i \text{weather}_{c_j} + \beta_0 + \beta_1 t_j + \beta_2 t_j^2 + \beta_3 t_j^3$$

Best model determined using F-tests

y_{ij} = predicted yield of farm i at time t_j ; t_j = time index, with $t_1 = 1$ in 1980
 β_0 = modeled intercept of farm i ; α_i = parameter specific for each farm i
 weather $_{c_j}$ = different weather indices, depending on county c and time t_j

RESULTS

- Trend estimation and aggregation level (Tab. 1)
 - With higher aggregation level, trend estimations are more stable and less dependent on detrending technique and the use of weather information
- Trend estimation and detrending technique
 - In 29% different trend estimations found between OLS and MM with reduced form models (Tab. 2).
 - In 19% different trend estimations found between OLS and MM with full models (Tab. 2).
 - In general higher order trends for MM than for OLS (Tab. 1 / 2).
- Inclusion of weather information at the farm level
 - In 32% different trend estimations found between reduced and full model with OLS (Tab. 2).
 - In 34% different trend estimations found between reduced and full model with MM (Tab. 2).
 - In general higher order trends for the full model than for the reduced model (Tab. 1 / 2).

Tab. 1 Trend estimations at different trend aggregation levels

	OLS full	OLS reduc.	MM full	MM reduc.
Rayon 1	3	0	3	3
Rayon 2	0	0	0	0
Rayon 3	0	0	0	0
Rayon 4	2	0	2	0
Rayon 5	0	0	0	0
Rayon 1 (*)	0	0	3	0
Rayon 2 (*)	0	0	3	0
Rayon 3 (*)	0	0	2	0
Rayon 4 (*)	2	1	2	2
Rayon 5 (*)	0	0	0	0
Oblast 1	0	0	0	0
Oblast 2	2	0	2	0
National yield	-	2	-	2

*0: no trend, *1: linear trend, *2: quadratic trend, *3: cubic trend.
 Rayon 1-Rayon 5: county yield data; Rayon 1 (*) - Rayon 5 (*) samples of area weighted farm yield data from a rayon, Oblast = regional data.

Tab. 2 Trend estimations at farm level

	OLS full / OLS reduced Total diff: 32%				MM full / MM reduced Total diff: 34%				No identical time trend: OLS full vs. MM full / OLS reduc. vs. MM reduc.
	No trend	Linear trend	Quadratic trend	Cubic trend	No trend	Linear trend	Quadratic trend	Cubic trend	
Rayon 1	2/3	2/2	3/3	5/4	3/3	1/2	1/2	7/5	3/3
Rayon 2	4/9	2/1	0/0	5/1	4/6	2/3	0/0	5/2	2/3
Rayon 3	4/4	2/2	1/1	0/0	3/4	1/1	2/1	1/1	2/3
Rayon 4	0/3	2/6	8/1	0/0	0/1	1/5	7/3	2/1	2/4
Rayon 5	7/7	0/0	0/0	0/0	7/6	0/0	0/0	0/1	0/1
Total	17/26	8/11	12/5	10/5	17/20	5/11	10/6	15/10	9/14

Numbers in the table indicate the numbers of farms with the respective trend estimations.

DISCUSSION

- Aggregated data could not satisfy the high heterogeneity present among the farms.
- The choice of the detrending method led to substantial differences in the detrended yield estimations. In the above described framework of extremely volatile yield time series in transition or developing countries, robust regression techniques may be highly relevant.
- Adding a weather variable representing prevailing weather conditions during the crop growing season as an additional regressor may help to reduce over- and underestimation of technological trends. Additionally, weather variables might themselves exhibit a significant trend due to climate change. Ignoring such trends and using a reduced trend model might lead to inconsistent estimates of the trend parameters as the model residuals would not be independent from trend model regressors, i.e. time variable(s).

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