Agro-Ecosystem Productivity and the Dynamic Response to Shocks

by

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Motivations

- Dynamics is at the heart of economic development and the search for processes that contribute to improving human welfare.
- But dynamic processes are typically complex, especially under nonlinear dynamics and unanticipated shocks.
- Under some scenarios, the effects of adverse shocks matter in the short run but dissipate in the longer run.
- But under other scenarios, the longer term impacts of **adverse shocks** can be **sustained and large**. **Examples**:
  - **Poverty traps** which associate poverty with reduced investment and meager prospects for economic growth (e.g., Barrett and Carter, 2013; Kraay and McKenzie, 2014).
  - **Ecological collapse**: when an ecosystem fails to recover under extreme shocks (e.g., Holling, 1973; Common. and Perrings, 1992; Perrings, 1998; Gunderson, 2000; Folke et al., 2004; Derissen et al., 2011).
  - **Economic collapse** with large and lasting adverse effects on society (e.g., Tainter, 1990; Diamond, 2005).
- In these examples, the outcomes are all undesirable. But the assessment of these situations can be challenging for two reasons: 1/ such adverse scenarios may not be very common; and 2/ the dynamics of the underlying process is often complex and poorly understood.
- This provides the main motivations for this paper:
  - First, we need to refine our tools used in dynamic stochastic analysis.
  - Second, we need to explore applications that provide new insights into economic dynamics.

Overview

- This paper investigates the nonlinear dynamic response to shocks, relying on a **threshold quantile autoregression (TQAR)** model as a flexible representation of stochastic dynamics.
- **The TQAR model can identify zones of stability/instability and characterize resilience and traps**.
    - **Resilience** means high odds of escaping from undesirable zones of instability toward zones that are more desirable and stable.
    - **Traps** mean low odds of escaping from zones that are both undesirable and stable.
- The approach is illustrated in an application to the **dynamics of productivity applied to historical data on wheat yield in Kansas** over the period 1885-2012.
- The dynamics of this agroecosystem and its response to shocks are of interest as Kansas agriculture faced **major droughts**, including the **catastrophic Dust Bowl** of the 1930's.
- The analysis identifies a **zone of instability in the presence of successive adverse shocks**.
- It also finds evidence of **resilience**. We associate the resilience with **induced innovations in management and policy response to adverse shocks**.

Dynamics

- Consider a dynamic system where the variable y_t evolves according the m-th order stochastic difference equation

$$y_t = f(y_{t-1}, \ldots, y_{t-p}, e_t), \qquad (3)$$

and e_t is a random variable representing unobservable effects at time t.

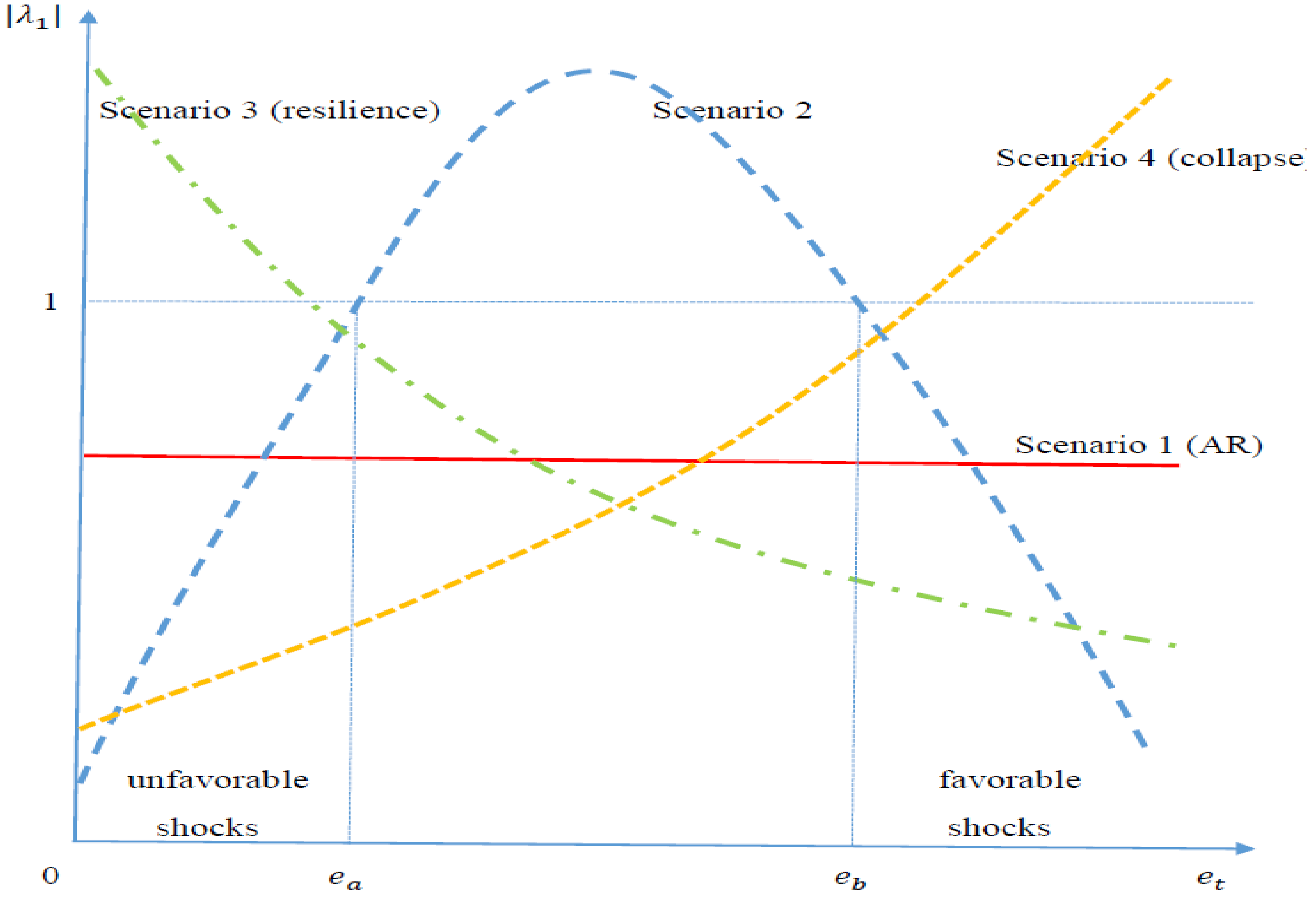
- The reduced form equation (3) can be written as the first-order difference equation

$$w_t \equiv \begin{bmatrix} y_t \\ \vdots \\ y_{t-m+1} \end{bmatrix} = \begin{bmatrix} f(y_{t-1}, \ldots, y_{t-m}, e_t) \\ \vdots \\ y_{t-m+1} \end{bmatrix} \equiv H(w_{t-1}, e_t) \qquad (4)$$

where $w_t \in \mathbb{R}_+^m$.

- Let $DH(w_{t-1}, e_t) = \partial H(w_{t-1}, e_t)/\partial w_{t-1}$ be a ($m \times m$) matrix with characteristic roots $[\lambda_1(w_{t-1}, e_t), \ldots, \lambda_m(w_{t-1}, e_t)]$,
- $\boldsymbol{\lambda_1(w_{t-1}, e_t)}$ **is the dominant root of** $\boldsymbol{DH(w_{t-1}, e_t)}$.
- $\ln(|\lambda_1(w_{t-1}, e_t)|)$ is the **rate of divergence** of y_t along forward paths in the neighborhood of (w_{t-1}, e_t).
- The system is **locally stable (locally unstable)** at point (w_{t-1}, e_t) if $|\boldsymbol{\lambda_1(w_{t-1}, e_t)}| \boldsymbol{< 1\ (> 1)}$.

Figure 1: Dynamic Patterns for the dominant root $|\lambda_1|$



Econometrics

- Consider the case where equation (3) takes the general form

$$y_t = f(y_{t-1}, \ldots, y_{t-m}, x_t, e_t)$$

where x_t is a vector of explanatory variables affecting y_t at time t.

- Define the **conditional distribution function** of y_t as

$$F(v \mid y_{t-1}, \ldots, y_{t-m}, x_t) = Prob[f(y_{t-1}, \ldots, y_{t-m}, x_t, e_t) \leq v].$$

- Define the associated **conditional quantile function** as the inverse function $q(r \mid y_{t-1}, \ldots, y_{t-m}, x_t) \equiv inf_v \{v: F(v \mid y_{t-1}, \ldots, y_{t-m}, x_t) \geq r\}$

  where $r \in (0,1)$ is the r^{th} quantile.

- Both the distribution function $F(v \mid y_{t-1}, \ldots, y_{t-m}, x_t)$ and the quantile function $q(r \mid y_{t-1}, \ldots, y_{t-m}, x_t)$ are generic: they provide a complete characterization of the dynamics of y under

The TQAR model

- Assume that conditional quantile function takes the form

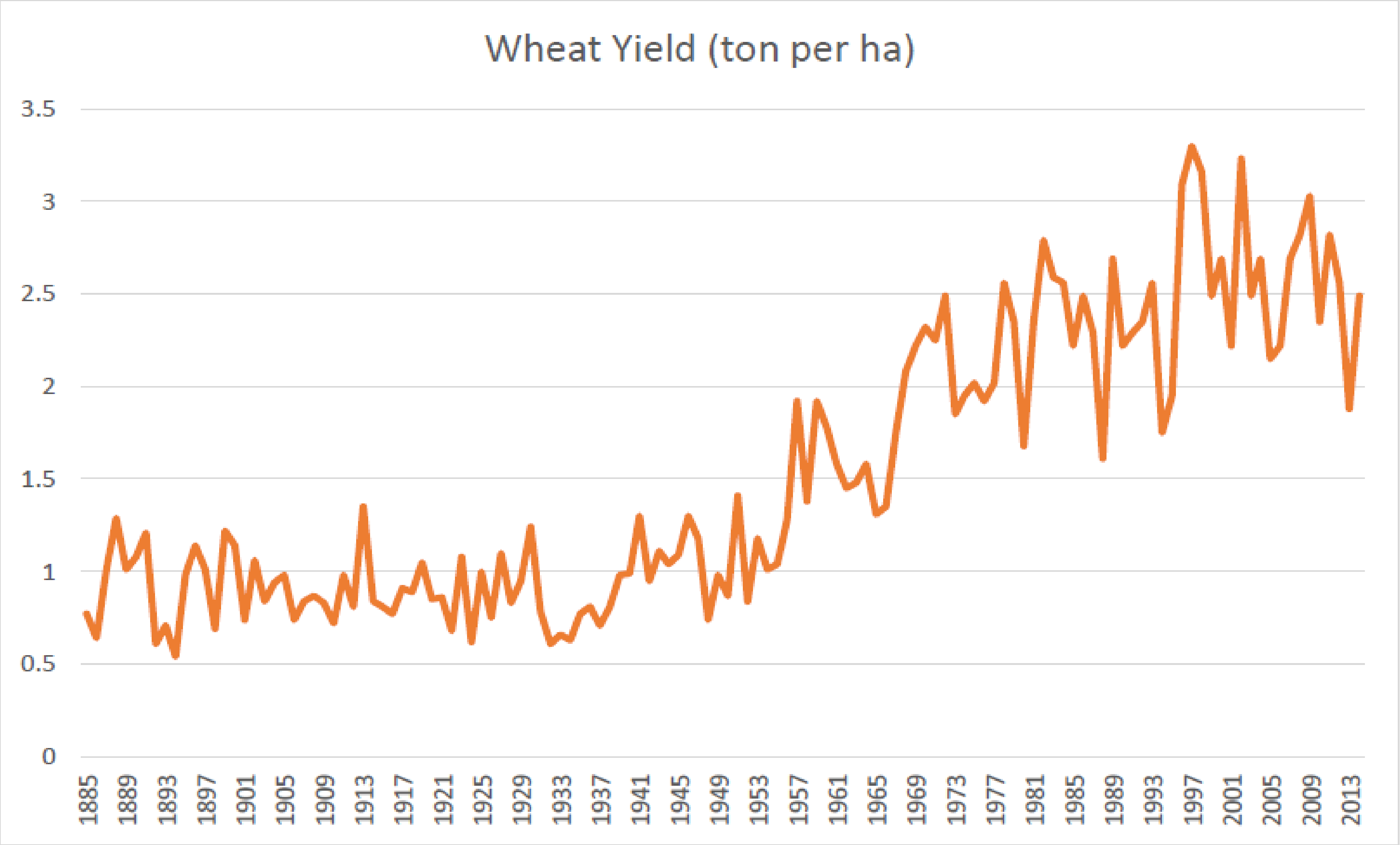
$$q(r\,|\,y_{t-1},\dots,y_{t-m},x_t)=\beta_0(r,x_t)+\sum_{j=1}^{m}\beta_j(r,x_t)\,y_{t-j}\,. \qquad (6)$$

- Define $d_{k,t-j}=\begin{cases}1\\0\end{cases}$ when $y_{t-j}\begin{cases}\in S_k\\ \notin S_k\end{cases}$, $k=1,\dots,K$, $j=1,\dots,m$, where $\{S_1,\dots,S_K\}$ is a partition of $\mathbb{R}$. This identifies ***K*** **regimes** $(S_1,\dots,S_K)$ with the $d_{k,t-j}'s$ being variables capturing the switch between regimes, $j=1,\dots,m$.
- When x_t includes the variables $d_{k,t-j}'s$, the autoregression parameter $\beta_j(r,x_t)$ can vary across the K regimes, $j=1,\dots,m$. Then (6) is the **Threshold Quantile Autoregressive (TQAR(m))** model (Galvao et al., 2011; Chavas and Di Falco, 2016).
- The **TQAR(m) model in (6) is flexible** in the sense that the autoregression parameter $\beta_j(r,x_t)$ in (6) can vary with current shock (as captured by the quantile r) and with the lagged value y_{t-j} (as captured by the regime-switching variables $d_{k,t-j}'s$).
- The **TQAR(m) model includes as special cases**:
  - The standard **Autoregressive model** of order m, AR(m), when $\beta_j(r,x_t)=\beta_j$, $j=1,\dots m$).
  - the **Threshold Autoregression** (TAR(m)) model when $\beta_j(r,x_t)=\beta_j(x_t)$, $j=1,\dots,m$ (Tong, 1990)
  - the **Quantile Autoregressive model** QAR(m) when $\beta_j(r,x_t)=\beta_j(r)$, $j=1,\dots m$ (Koenker and Xiao, 2006)
- The **TQAR(m) model in (6) can be estimated as a quantile regression model** (Koenker, 2005).

An Application to Wheat Productivity in Kansas

- The empirical analysis involves annual **wheat yield in Kansas** over the period 1885-2012 (USDA, 2015).
- Kansas, the largest wheat producer in the US, has seen several **major droughts**.
- The analysis covers the period of the **American Dust Bowl** (in the 1930's) when the US Great Plains were affected by a **major environmental catastrophe** (Hornbeck, 2012).
- **The Dust Bowl was the joint product of adverse weather shocks (a major drought) and poor agricultural management**.
- The Dust Bowl is remembered by two of its main features:
  - 1/ severe drought leading to crop failure and triggering massive migration out of the western Great Plains
  - 2/ soil and wind erosion inducing a large decline in agricultural productivity (Hornbeck, 2012).

Figure 2: Kansas Wheat Yield (ton per ha)



Preliminary Analysis

- With wheat yield y_t as the dependent variable, we first estimate simple **autoregressive models**.
- **Two time trend variables** are included in all models:
  - a general time trend $t = year - 2000$
  - a time trend $t_1 = \begin{cases} 0 \\ year - 1935 \end{cases}$ when $year = \begin{cases} < 1935 \\ \geq 1935 \end{cases}$, where t_1 captures technological progress after 1935.
- Table 1 reports **autoregressive models of order m**, AR(m), with m = 1, 2.
- The AR(1) model shows that lag-1 coefficient is 0.703 and highly significant. **This documents the presence of dynamics in yield adjustments**.
- The lagged-2 coefficient in the AR(4) model is not statistically significant. A Wald test of the AR(1) model as a null hypothesis against the AR(2) model gave a p-value of 0.709, indicating that there is no significant dynamics going beyond one-period lag.
- Table 1 also reports **threshold autoregressive models** (TAR(m)) allowing the autoregression parameters to vary across **three regimes** (d_1, d_2, d_3). The regimes are defined such that

  $$d_{i,t} = \begin{cases} 1 \\ 0 \end{cases} \text{ when } y_t \begin{cases} \in S_{i,t} \\ \notin S_{i,t} \end{cases}, \; i = 1,2,3,$$

  with $S_{1,t} = [-\infty, b_{1,t}]$, $S_{2,t} = (b_{1,t}, b_{3,t}]$ and $S_{3,t} = (b_{3,t}, \infty]$, $b_{1,t}$ and $b_{3,t}$ being respectively the **$1/3$ and $2/3$ quantile of the yield distribution** obtained from the AR(1) model.
- Table 1 shows **evidence of threshold effects** as the coefficient of $(d_{1,t-1} \, y_{t-1})$ is statistically significant.

Table 1: Estimates of Autoregressive Models

Paramaters	AR(1)	AR(2)	TAR(1)	TAR(2)
Intercept	0.703***	0.706***	0.543***	0.540**
y_{t-1}	0.236***	0.219**	0.409**	0.463**
y_{t-2}		0.034		-0.039
$d_{1,t-1} * y_{t-1}$			0.098*	0.111*
$d_{3,t-1} * y_{t-1}$			-0.010	-0.018
$d_{1,t-2} * y_{t-2}$				-0.020
$d_{3,t-2} * y_{t-2}$				-0.011
t	-0.002	-0.003	-0.002	-0.002
t_1	.0023***	0.024***	0.017**	0.017**
R^2	0.857	0.856	0.859	0.860

Note: Asterisks indicate the significance level: * for the 10 percent significance level; *** for the 5 percent significance level; and *** for the 1 percent significance level.

Quantile Dynamics

- We estimated a **TQAR(1) model applied to Kansas wheat yield**
- The estimates are reported in Table 2 for selected quantiles $(0.1, 0.3, 0.5, 0.7, 0.9)$.
- Table 2 shows that **dynamics vary across quantiles**. The null hypothesis that the regression parameters are the same across quantiles was strongly rejected.
- This implies a strong rejection of the TAR(1) model in favor of the TQAR(1) model.
- Table 2 also shows that **dynamics vary across regimes**. At the 0.1 quantile, we strongly reject the null hypothesis that the lag-1 coefficient is the same across regimes.
- This implies a strong rejection of the QAR(1) model in favor of the TQAR(1) model.
- Thus, table 2 documents that **dynamics vary both across quantiles and across regimes**.
- The lag-1 coefficient for the 0.1 quantile is 0.921 under regime 1 (when lagged yield is low), which is much higher than under the other regimes. This documents the presence of **much stronger dynamics in the lower tail of yield distribution and when lagged yield is low**. This is one of our key findings: **dynamic yield adjustments to shocks become quantitatively different under repeated adverse shocks**.

Table 2: Estimates of Threshold Quantile Autoregressive Model TQAR(1) for Selected Quantiles

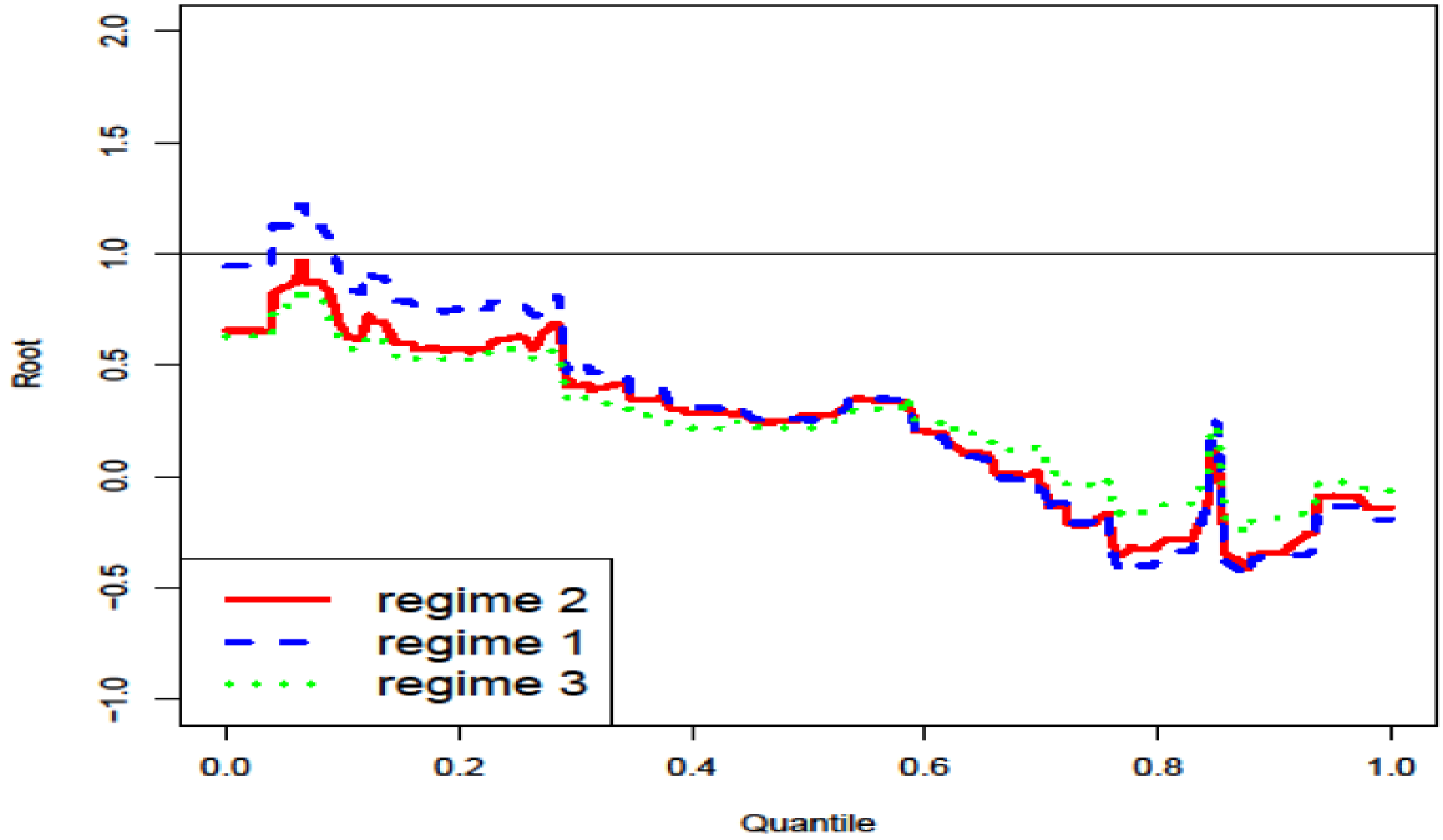
Parameters	quantile				
	r = 0.1	r = 0.3	r = 0.5	r = 0.7	r = 0.9
Intercept	-0.003	0.481**	0.747***	1.036***	1.409***
y_{t-1}	0.687***	0.407	0.272	-0.036	-0.341
$d_{1,t-1} * y_{t-1}$	0.234***	0.086	-0.015	-0.026	-0.007
$d_{3,t-1} * y_{t-1}$	-0.067	-0.057	-0.051	0.125	0.156
t	0.000	-0.003	-0.005**	-0.005**	-0.001
t_1	0.003	0.018**	0.027***	0.035***	0.040***

Note: Hypothesis testing is conducted using bootstrapping. Asterisks indicate the significance level: * for the 10 percent significance level; *** for the 5 percent significance level; and *** for the 1 percent significance level.

Implications

- Using equation (4), we examine the dynamic properties of our estimated TQAR(1) by evaluating the associated root $\lambda = \partial H / \partial y_{t-1}$. Under nonlinear dynamics, **this root varies with the situation considered**.
- Recall that dynamics is **locally stable (unstable) at points where $\boldsymbol{\lambda} < \mathbf{1}$ $(> \mathbf{1})$**.
- After estimating the model for all quantiles, we calculated the root λ for all quantiles and all three regimes. The results are reported in Figure 4.
- Figure 4 documents the **patterns of nonlinear dynamics** associated with our TQAR(1) model.
- Figure 4 shows that the root λ is similar across all three regimes for quantiles greater than 0.3. But **the root $\boldsymbol{\lambda}$ exhibits different dynamics for lower quantiles** (less than 0.3). More specifically, compared to other regimes, **the root $\boldsymbol{\lambda}$ is larger under regime 1 (when lagged yield is low) <u>and</u> in the lower tail of the distribution**.

Figure 4: Root of the Dynamic Yield Equation



Implications (2)

- Figure 4 shows that the root λ remains in the unit circle (with $|\lambda|<1$) in many situations, including regimes 2 and 3 (when lagged yield are not low) or the absence of adverse current shock (for quantiles greater than 0.2). This implies that **the system is locally STABLE in many situations, especially in situations EXCLUDING adverse shocks**. This is an important result: investigating dynamics in situations around or above the median could only uncover evidence of local stability. This would preclude finding any evidence of traps.
- Figure 4 shows that the root λ can be larger than 1 but only in situations of successive adverse shocks, i.e. when both y_t and y_{t-1} are in the lower tail of the yield distribution. Associating $\lambda>1$ with local instability, we thus find **evidence of local instability in the presence of adverse shocks**.
- **Thus, we have identified a zone of local dynamic instability and found that this zone is associated with successive adverse shocks**. This raises the question: Is the zone of instability associated with resilience? Or is it associated with a trap or collapse? It depends on the path of escape.
- As discussed above, if the escape from the zone of instability is toward more favorable situations, the system would be characterized as **resilient** (e.g., as represented by Scenario 3 in Figure 1). Alternatively, if the escape is toward more unfavorable situations, the system may be experiencing a **trap** or a **collapse** (e.g., Scenario 4 in Figure 1).

Implications (3)

- The zone of instability occurs only under successive unfavorable shocks generating very low yields. It suggests that starting in this zone, there is only one place to go: toward higher yields. This suggests that our zone of instability is associated with a **resilient system that tends to escape from low productivity toward higher productivity under adverse shocks**.
- Indeed, Figure 4 exhibits patterns that are similar to Scenario 3 in Figure 1.
- Our results uncover evidence of a **dynamic escape from unfavorable events located in the lower tail of the distribution**. Since escaping an unfavorable zone is the essence of resilience, if follows that **our analysis documents the presence of resilience**.
- In other words, our estimated TQAR(1) model applied to wheat yield dynamics has two key characteristics: 1/ a zone of instability occurs in the presence of successive unfavorable shocks; and 2/ resilience arises as the underlying dynamic process tends to escape from this unfavorable zone.

Discussion

- Farming in the Western Great Plains faces much rainfall uncertainty and it has experienced repeated periods of **severe droughts** (Burnette and Stahle, 2013). One of the most severe drought occurred in the 1930's: it led **massive crop failures and to the Dust Bowl**.
- Because of the massive soil erosion it generated, the Dust Bowl is often seen as an **environmental catastrophe** (Hornbeck, 2012). Yet, our evidence of resilience suggests a **different interpretation**.
- The Dust Bowl induced significant changes in agricultural management and policy. A major federal policy change was the creation of the Soil Conservation Service (SCS) in 1935. The SCS played a major role of reducing the incidence of wind erosion in the Western Great Plains (Hurt, 1981).
- Thus, **we associate our evidence of resilience with induced innovations in both policy and management that followed the Dust Bowl**.

Discussion (2)

Our analysis has important implications.

- First, evaluating resilience/collapse/traps must focus on **the nature of dynamics under adverse shocks**. As noted above, just knowing what is happening “on average” is not sufficient.
- Second, **the assessment of local instability is crucial**. Our TQAR approach provides a great analytical framework to conduct this assessment.
- Third, in general, the dynamic response to adverse shocks depends on management and policy. Our discussion has pointed out the role of innovations. On the negative side, collapse/traps are more likely to arise in the absence of management and policy response to adverse shocks. On the positive side, **induced innovations in management and policy can be a crucial part of designing a more resilient system**.

Thus, **our analysis indicates the important role played by the induced response of management and policy to adverse shocks**.

Conclusion

- This paper has studied the **dynamic response to shocks**, with an application an agro-ecosystem productivity. It has proposed a **threshold quantile autoregression** (TQAR) model as a flexible representation of stochastic dynamics. It has focused on the identification of **zones of local instability and their usefulness in the characterization of resilience and traps**.
- The usefulness of the approach was illustrated in an application to the dynamics of wheat yield in Kansas. The analysis examined the effects of extreme shocks both in the short run and in the long run. It identified a **zone of instability in the presence of successive adverse shocks**. It also found evidence of **resilience**. We associate the **resilience with induced innovations in management and policy in response to adverse shocks**.
- Our approach is generic and can be applied to the analysis of dynamics in any economic system. This motivates a need to extend our analysis and its applications to other economic conditions.