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Chapter Author(s): Jean-Paul Chavas

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Agroecosystem Productivity and the Dynamic Response to Shocks

Jean-Paul Chavas

8.1 Introduction

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. Indeed, nonlinear dynamic systems can exhibit many patterns. For deterministic systems, this can go from reaching a unique steady state to having multiple steady states, to displaying limit cycles, or even to being chaotic (e.g., May 1976). For stochastic systems the complexity increases further, making it challenging to evaluate the dynamic response to unanticipated shocks. The assessment of such dynamic response is highly relevant in economics. Some shocks are favorable (e.g., good weather, the discovery of new knowledge) with positive impacts on welfare both in the short run and the longer run. But other shocks have a negative impact on human welfare (e.g., drought, disease). The dynamic effects of such shocks has been of great interest to economists and policymakers. Under some scenarios, their adverse effects matter in the short run but dissipate in the longer run. But under other scenarios, their longer-term impacts can be sustained and large. An example is the case of poverty traps, which associate poverty with meager prospects for economic growth (e.g., Dasgupta 1997; Azariadis and Stachurski 2005; Barrett and Carter 2013; Kraay and McKenzie 2014; Barrett and Constas 2014). Another example is from ecology: under some circumstances, an

Jean-Paul Chavas is the Anderson-Bascom Professor of Agricultural and Applied Economics at the University of Wisconsin–Madison and a member of the board of directors of the National Bureau of Economic Research.

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ecosystem may fail to recover under extreme shocks (e.g., Holling 1973; Common and Perrings 1992; Perrings 1998; Gunderson 2000; Folke et al. 2004; Derissen, Quaas, and Baumgärtner 2011). Other examples include cases of economic collapse with large and lasting adverse effects on society and civilization (e.g., Tainter 1990; Diamond 2005). This includes the case of ancient Egypt, where failures of the Nile floods caused great famines that imperiled Nile civilizations (e.g., Shaw 2000; Marriner et al. 2012). This also includes widespread droughts that contributed to the collapse of Classic Mayan civilization in Central America between 800 to 1000 AD (Gill 2000; Webster 2002; Medina-Elizalde and Rohling 2012). Adverse weather shocks remain relevant today as they threaten food production and food security around the world (e.g., Headey 2011; Nelson et al. 2014; Kalkuhl, von Braun, and Torero 2016). In these examples, the shocks are all undesirable. But the assessment of these situations can be challenging for two reasons: (a) such adverse scenarios are not very common, and (b) the dynamics of the underlying process is often complex and poorly understood. This suggests two useful directions of inquiry. First, we need to refine our tools used in dynamic analysis. Second, we need to explore applications that may provide new insights into economic dynamics. These two directions are key motivations for this chapter.

This chapter studies nonlinear dynamics in economics. It makes three contributions. First, the analysis evaluates the linkages between stochastic dynamics and the characterization of resilience and traps. Resilience means good odds of escaping from undesirable zones of instability toward zones that are more desirable. Traps mean low odds of escaping from zones that are both undesirable and stable. As such, resilience is desirable but traps are not. As noted above, the measurement and evaluation of dynamics associated with traps or resilience remains difficult (e.g., Barrett and Constas 2014). Our analysis focuses on identifying zones of stability/instability that provides a good basis to evaluate the resilience of a system and the presence of traps.

Second, the investigation of resilience and traps requires a refined approach to the study of stochastic dynamics, with a special focus on representations that allow for flexible dynamic response to shocks. The chapter relies on a threshold quantile autoregressive (TQAR) model (Galvao, Montes-Rojas, and Olmo 2011; Chavas and Di Falco 2017). The TQAR model is empirically tractable. And it is flexible: it allows dynamics to vary with both current shocks and past states. As such, a TQAR model can be used to assess how dynamics can differ across situations (as reflected by different shocks and different states). This makes it particularly appropriate for our purpose.

A third contribution is to illustrate the usefulness of our approach in an application to the dynamics of an agroecosystem. Our empirical analysis uses historical data on wheat yield in Kansas during the period 1885–2012. Historically, the western Great Plains have experienced many periods of severe drought (Burnette and Stahle 2013). The worse drought occurred in the 1930s leading to the Dust Bowl, a major American environmental catastrophe (Hornbeck 2012). Coupled with intensive land use, the drought led to major crop failure, wind erosion, and dust storms. The impact was particularly severe in Kansas, where land erosion contributed to significant decrease in land value and agricultural productivity (Hornbeck 2012). The short-run response to the environmental destruction was mostly population migration away from the affected areas, but the long-run effects were major and lasting. Hornbeck (2012) documents that soil erosion due to the Dust Bowl contributed to a decline in land value up to 30 percent in the long term. Wheat being the major crop in Kansas (USDA 2015), studying Kansas wheat yield provides a great case study of the dynamic response to environmental shocks. Of special interest are the effects of extreme shocks both in the short run and in the long run. In the context of wheat yield, our 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 in response to adverse shocks. This stresses the importance of management and policy in the dynamic response to shocks.

The chapter is organized as follows. Section 8.2 presents a general model of stochastic dynamics and examines its linkages with traps and resilience. Section 8.3 introduces a threshold quantile autoregressive model and its flexible representation of the dynamic effects of shocks. Section 8.4 presents an econometric application to the dynamics of wheat productivity in Kansas. Implications and discussion of the results are the topic of sections 8.5 and 8.6. Finally, section 8.7 concludes.

8.2 Dynamics, Traps, and Resilience

Consider a dynamic system evolving according to the state equations

$$y_t = h(y_{t-1}, \ldots, y_{t-p}, z_t), \tag{1a}$$

$$z_t = g(y_{t-1}, \ldots, y_{t-p}; z_{t-1}, \ldots, z_{t-p}), \tag{1b}$$

where $y_t \in \mathbb{R}$ measures payoff at time t, z_t is a vector of variables affecting the system with dynamics given in equation (1b), and $p \geq 1$. Equations (1a) and (1b) provide a general representation of dynamics, allowing for joint dynamics in payoff y_t and in the state variables z_t. After successive substitutions of equation (1b), note that equation (1a) can be alternatively written as

$$\begin{aligned} y_t &= h\,(y_{t-1}, y_{t-2}, \ldots, g\,(y_{t-1}, y_{t-2}, \ldots; z_{t-1}, z_{t-2}, \ldots)) \\ &= h(y_{t-1}, y_{t-2}, \ldots, g(y_{t-1}, y_{t-2}, \ldots; g(y_{t-2}, \ldots; z_{t-2}, \ldots), z_{t-2}, \ldots)) \\ &= \ldots \\ &= f_0(y_{t-1}, y_{t-2}, \ldots; y_0, z_0) \end{aligned} \tag{2}$$

where (y_0, z_0) are initial conditions, which we take as given. Assume that the effects of lagged values of y_{t-j} on y_t in equation (2) become negligible for all $j > m$. It follows that equation (2) can be written as

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

and e_t is a random variable representing unobservable effects at time t. We assume that e_t is identically and independently distributed[1] with a given distribution function.

Equation (3) is an mth order stochastic difference equation representing economic dynamics under general conditions. Comparing equations (1) and (3), equations (1a) and (1b) are structural equations describing how the system evolves over time, while equation (3) is a reduced-form equation of the same system. While equation (3) does not reflect structural information about the system, it has two advantages: (a) it provides a valid representation of the system dynamics, and (b) it does not require information about the variables z_t. This is a significant advantage when some of the dynamic factors affecting payoff are not observable. For this reason, our analysis will focus on the reduced-form representation (3).

Note that equation (3) can be written as the first-order difference equation

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

where $w_t \in \mathbb{R}^m_+$. Equation (4) can be used to characterize the nature of dynamics. Under differentiability, let $DH\,(w_{t-1}, e_t) = \partial H\,(w_{t-1}, e_t) \,/\, \partial w_{t-1}$ be an $(m \times m)$ matrix. Denote the characteristic roots of $DH\,(w_{t-1}, e_t)$ by $[\lambda_1(w_{t-1}, e_t), \ldots, \lambda_m(w_{t-1}, e_t)]$ where $|\lambda_1(w_{t-1}, e_t)| \geq \ldots \geq |\lambda_m(w_{t-1}, e_t)|$, $|\lambda_j|$ being the modulus of the jth root, $j = 1, \ldots, m$, and λ_1 being the dominant root.

Where equation (3) is linear in $(y_{t-1}, \ldots, y_{t-m})$, the system exhibits linear dynamics. In this case, the matrix DH is constant and so are its roots $(\lambda_1, \ldots, \lambda_m)$. Consider for a moment a situation where e_t is constant for all t. Then, under linear dynamics, the system is globally stable (in the sense that $\lim_{t\to\infty} y_t = y^e$ for any initial condition y_0) if $|\lambda_1| < 1$ (Hasselblatt and Katok 2003). Alternatively, the system would be unstable if $|\lambda_1| > 1$. When λ_1 is real, the dynamics of y_t has a forward path that is $\left\{\begin{smallmatrix}\text{exponential}\\ \text{oscillatory}\end{smallmatrix}\right\}$ when $\lambda_1 \left\{\begin{smallmatrix}>0\\ <0\end{smallmatrix}\right\}$. And when λ_1 is complex, then $\lambda_1 = a + b\sqrt{-1}$ and the system exhibits cyclical dynamics, with a cycle of period $[2\pi \,/\, arctg\,(b \,/\, a)]$.

In the general case where equation (3) is nonlinear in $(y_{t-1}, \ldots, y_{t-m})$, the system exhibits nonlinear dynamics. Under nonlinear dynamics, the forward path of y_t can exhibit a variety of dynamic patterns. For example, holding

1. Note that assuming serial independence of e_t is not restrictive since any serial correlation can be captured by the dynamic equation for z_t in equation (1b).

e_t constant for all t, y_t can eventually reach a unique steady state, it can have multiple steady states, it can exhibit limit cycles, or it can be chaotic (e.g., May 1976). Situations of multiple steady-state equilibria have been of interest. Multiple steady states $(y_1^e, \ldots, y_M^e)$ would arise if $\lim_{t\to\infty} y_t = y_j^e$ when $y_0 \in S_j$, $j = 1, \ldots, M$, where $M > 1$ and $(S_1, \ldots, S_M)$ is a partition of $\mathbb{R}$. In this context, the set S_j is the attractor of point y_j^e, $j = 1, \ldots, M$, as having initial condition y_0 in S_j eventually leads to y_j^e, $j = 1, \ldots, M$. When a steady state y_j^e is identified as being "undesirable," it means that it is good to avoid being in the set S_j. Examples include cases of ecological collapse in ecology (Holling 1973) and poverty trap in economics (Barrett and Carter 2013; Kraay and McKenzie 2014).

Under nonlinear dynamics, both $DH(w_{t-1}, e_t)$ and the dominant root $\lambda_1(w_{t-1}, e_t)$ depend on the evaluation point (w_{t-1}, e_t). In general, $\ln(|\lambda_1(w_{t-1}, e_t)|)$ measures the rate of divergence in y_t along forward paths in the neighborhood of (w_{t-1}, e_t) (Hasselblatt and Katok 2003). In this context, the dynamic properties just discussed still apply but only locally, that is, in the neighborhood of (w_{t-1}, e_t): the dynamics is locally stable if the dominant root satisfies $|\lambda_1(w_{t-1}, e_t)| < 1$, and it is locally unstable if $|\lambda_1(w_{t-1}, e_t)| > 1$. We will make use of these local properties in our empirical analysis below.

The analysis of dynamics becomes more challenging in the stochastic case: the random vector e_t in equation (3) affects the path of y_t over time. This is relevant when e_t represents unanticipated shocks. In this context, a key question is: What is the dynamic response of the system (3) to a shock e_t? This is the essence of the concept of resilience. A resilient system is defined as a system that can recover quickly from a shock (Holling 1973). This gains importance in the presence of adverse shocks (Di Falco and Chavas 2008; Chavas and Di Falco 2017). For example, in ecology, a resilient system would recover quickly from an adverse shock by moving away from undesirable situations and toward more desirable ones, but a nonresilient system may collapse. Similarly, in economics, a resilient household would recover quickly from an adverse income shock, but a nonresilient household would not (e.g., Barrett and Constas 2014). While adverse shocks always have negative short-term effects, resilience means such effects would eventually disappear in the longer term. But nonresilient systems would behave differently: they would see persistent adverse long-term effects.

The dominant root $\lambda_1(w_{t-1}, e_t)$ provides useful insights on system dynamics. We discuss three cases. First, consider the case where $\lambda_1(w_{t-1}, e_t)$ is close to 0 for all (w_{t-1}, e_t). This system would exhibit little dynamics, and any shock would have minor or no long-term effects. In a second case, assume that $|\lambda_1(w_{t-1}, e_t)|$ is positive but less than 1 for all (w_{t-1}, e_t). Then, there would be a dynamic response to any shock. But having $|\lambda_1(w_{t-1}, e_t)| < 1$ means that the impact of a shock would die down over time and eventually disappear in the long term. In this case, the magnitude of the dominant root remains useful. Having $|\lambda_1(w_{t-1}, e_t)|$ close to 0 (close to 1) means a rapid (slow) decay of the temporal effects of a shock. In other words, a rise in $|\lambda_1(w_{t-1}, e_t)| \in (0, 1)$ corresponds to stronger impacts of a shock in the intermediate term. Third, consider the case where $|\lambda_1(w_{t-1}, e_t)|$ is greater than 1 for some (w_{t-1}, e_t). As discussed above, this corresponds to local instability in the neighborhood of (w_{t-1}, e_t). A possible situation is that this local instability varies with the neighborhood. To illustrate, consider a system where N_1, N_2, N_3 are three different neighborhoods where $|\lambda_1(w_{t-1}, e_t)| < 1$ when $(w_{t-1}, e_t) \in N_1 \cup N_3$, but $|\lambda_1(w_{t-1}, e_t)| > 1$ when $(w_{t-1}, e_t) \in N_2$. This system exhibits local stability in neighborhoods N_1 and N_3, but local instability in neighborhood N_2. Local instability in N_2 means that dynamics would tend to move y_t away from N_2. In situations where N_2 is surrounded by N_1 and N_3, this would identify points in N_2 as tipping points, that is, as points where y_t would tend to escape from as they move toward locally stable neighborhoods. In this case, knowing which locally stable neighborhood (N_1 or N_3) is more likely to be visited would be of interest. For example, if being in N_1 is seen as being undesirable, then an escape from N_2 to N_3 would be seen as a better scenario than moving from N_2 to N_1.

These patterns are illustrated in figure 8.1 under four scenarios. Figure 8.1 shows how $|\lambda_1|$ can vary with e_t, where higher (lower) values of e_t are interpreted as favorable (unfavorable) shocks. The first scenario is the case where λ_1 is constant. This occurs when the dynamic is represented by a linear autoregressive (AR) process, in which case the dynamic response to shocks does not depend on the situation considered. Scenarios 2–4 are associated with nonlinear dynamics where λ_1 is not constant. Scenario 2 exhibits a pattern where $|\lambda_1|$ has an inverted U-shape with respect to e_t, with a zone of instability (where $|\lambda_1| > 1$) surrounded by two zones of stability (where $|\lambda_1| < 1$): a favorable zone (where e_t is high) and an unfavorable zone (where e_t is low). It means that the forward path of y_t would tend to escape from the instable zone. And in the case where there is a low probability of escaping from the unfavorable stable zone, this would identify this zone as a trap. Scenario 3 shows a situation where there is a zone of instability, but it occurs only for low values of e_t. This is an example of resilience where the dynamics would move the system away from unfavorable outcomes. Finally, Scenario 4 shows a situation where there is a zone of instability but it occurs only for high values of e_t. This represents a collapse where the dynamics move the system away from favorable outcomes. These examples illustrate that many patterns of dynamics are possible.[2] Note that the dynamics would gain additional complexities when we note that $|\lambda_1(w_{t-1}, e_t)|$ can vary with both e_t and w_{t-1}. The empirical challenge to evaluating these complexities is addressed in section 8.3.

2. Indeed, there are many possible scenarios (e.g., Azariadis and Stachurski 2005). Other possible scenarios (not shown in figure 8.1) are when there is a zone of stability surrounded by zones of instability, or when instability is global (e.g., under chaos).

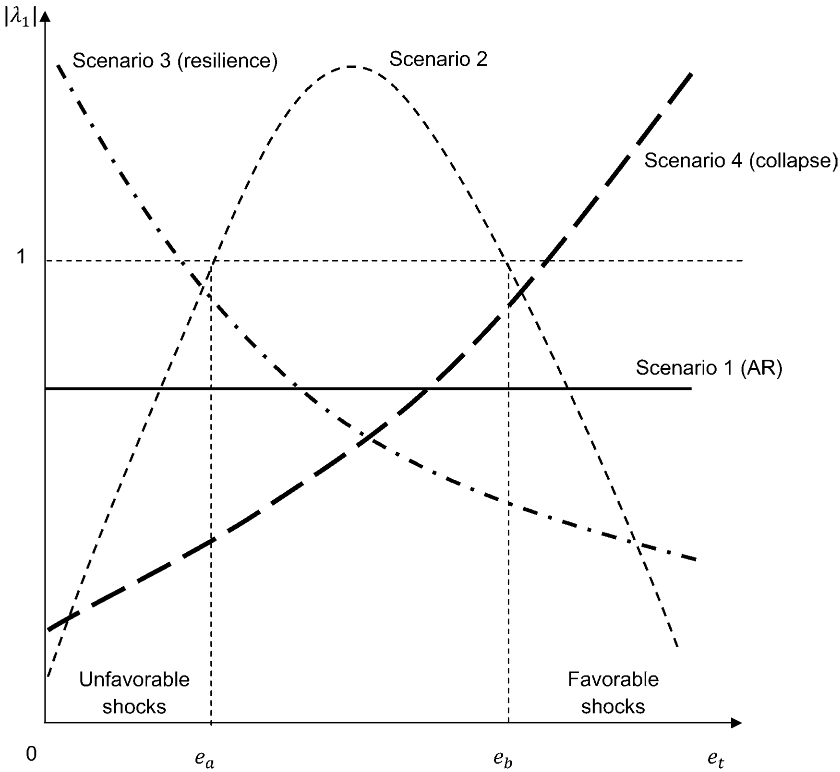

Fig. 8.1 Dynamic patterns for the dominant root $|\lambda_1|$

Under stochastic dynamics, a related issue is: What are the implications of dynamics for the distribution of y_t in the long run? To address this question, note that the dynamics in equation (3) can be alternatively written in terms of a Markov chain (Billingsley 1961; Meyn and Tweedie 1993). Consider partitioning the space $\mathbb{R}$ into K mutually exclusive intervals $\{v_1, \ldots, v_K\}$. To illustrate, consider the case where $m = 1$. Letting $M = \{1, \ldots, K\}$, we have

$$\text{(5a)}\quad \text{Prob}(y_t \in v_i) = \sum_{j \in M} \{\text{Prob}[y_t \in v_i \mid y_t = f(y_{t-1}, e_t), y_{t-1} \in v_j]\ \text{Prob}[y_{t-1} \in v_j]\}$$

for $i \in M$. Under time invariance, equation (5a) can be written as the Markov chain model

$$\text{(5b)}\qquad p_t = A p_{t-1}$$

where $p_t = (p_{t,1}, \ldots, p_{t,K})'$ is a $(K \times 1)$ vector with $p_{t,j} = \text{Prob}(y_t \in v_j)$, $j \in M$, and A is a $(K \times K)$ matrix of Markov transition probabilities. The

Markov matrix A has a dominant root equal to 1. Under time-invariant transition probabilities, when this dominant root is unique, the dynamic system (5b) has a unique stationary equilibrium given by $p^e = \lim_{t \to \infty} p_t$ for all initial conditions p_0. This provides a basis to evaluate the long-run distribution of y. This long-run distribution will depend on the underlying dynamics. Again, the long-run distribution of y can exhibit many patterns (Azariadis and Stachurski 2005). For example, the long-run probability density of y_t could exhibit a single peak with little skewness (e.g., under Gaussian shocks and a linear AR process). Alternatively, it could be skewed when the dynamics implies an escape from low outcomes (under resilience) or from high outcomes (under collapse). Finally, it could exhibit multiple peaks (e.g., when a system tends to escape from a zone of instability toward surrounding zones of stability, leading to a bimodal density in the long run). Again, these examples indicate that many patterns of long-run distribution are possible, stressing the importance of a flexible approach in the empirical investigation of dynamics.

8.3 Econometric Analysis of Stochastic Dynamics

Consider the case where equation (3) takes the general form $y_t = f(y_{t-1}, \ldots, y_{t-p}, x_t, e_t)$ where x_t is a vector of explanatory variables affecting y_t at time t. Define the conditional distribution function of y_t as $F(v \mid y_{t-1}, \ldots, y_{t-m}, x_t) = \text{Prob}[y_t \leq v \mid y_{t-1}, \ldots, y_{t-m}, x_t] = \text{Prob}[f(y_{t-1}, \ldots, y_{t-m}, x_t, e_t) \leq v]$. The distribution function $F(v \mid y_{t-1}, \ldots, y_{t-m}, x_t)$ is conditional on lagged values $(y_{t-1}, \ldots, y_{t-m})$ and on x_t. 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 rth quantile. When $r = 0.5$, this includes as special case the conditional median $q(0.5 \mid y_{t-1}, \ldots, y_{t-m}, x_t)$. 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 general characterization of the dynamics of y. In the rest of the chapter, we will make extensive use of the quantile function $q(r \mid y_{t-1}, \ldots, y_{t-m}, x_t)$ in the analysis of the dynamics of y_t.

Relying on the conditional quantile function $q(r \mid y_{t-1}, \ldots, y_{t-m}, x_t)$, we focus our attention on the case where the conditional quantile function takes the form $q(r \mid y_1, \ldots, y_{t-m}, x_t) = X(y_{t-1}, \ldots, y_{t-m}, x_t)\beta(r)$, $r \in (0, 1)$, where $X(\cdot)$ is a $(1 \times K)$ vector and $\beta(r) \in \mathbb{R}^K$ is a $(K \times 1)$ vector of parameters. This restricts the analysis to situations where conditional quantiles are linear in the parameters $\beta(r)$. This specification allows the parameters $\beta(r)$ to vary across quantiles, thus providing a flexible representation of the underlying distribution function and its dynamics. In addition, the function $X(y_{t-1}, \ldots, y_{t-m}, x_t)$ can possibly be nonlinear in $(y_{t-1}, \ldots, y_{t-m})$, thus allowing for nonlinear dynamics.

In the analysis presented below, we consider an econometric model specification of the form

$$(6)\qquad q(r \mid y_1, \ldots, y_{t-m}, x_t) = \beta_0(r, x_t) + \sum_{j=1}^{m} \beta_j(r, x_t) y_{t-j}.$$

To illustrate the flexibility of this specification, note that it reduces to a standard autoregressive model of order m, AR(m) (e.g., see Enders 2010), when $\beta_j(r, x_t) = \beta_j$, $j = 1, \ldots, m$, for all $r \in (0, 1)$ and all x_t, that is, when the autoregression parameters β_j's are constant and do not vary across quantiles. When the intercept $\beta_0(r, x_t)$ varies across quantiles r, this provides a flexible representation of the distribution function (e.g., it allows for any variance, skewness, and kurtosis). Also, when $\beta_0(r, x_t)$ varies with x_t, this allows x_t to shift the intercept. But an AR(m) model is restrictive in two important ways: (a) it is restricted to linear dynamics in the mean; and (b) it does not provide a flexible representation of dynamics in variance, skewness, or kurtosis. Such limitations have stimulated more general specifications capturing dynamics in variance (e.g., the generalized autoregressive conditional heteroscedastic [GARCH] model proposed by Bollerslev [1986]) and nonlinear dynamics (e.g., Markov switching models, Hamilton [1989]), threshold autoregressive (TAR) models (Tong 1990), and smooth transition autoregressive (STAR) models (Van Dijk, Teräsvirta, and Franses 2002).

When $\beta_j(r, x_t) = \beta_j(r)$, $j = 1, \ldots, m$, the above specification reduces to the quantile autoregressive model QAR(m) proposed by Koenker and Xiao (2006). Unlike an AR(m), the QAR(m) model allows the autoregression parameters $\beta_j(r)$ to vary across quantiles $r \in (0, 1)$, thus permitting dynamics to differ in different parts of the distribution. In the more general case, $\beta_j(r, x_t)$ can vary with the explanatory variables x_t, allowing economic conditions to affect dynamics.

In addition, considering the case where the state space $\mathbb{R}$ is partitioned into K subsets $\mathbb{R} = \{S_1, \ldots, S_K\}$, define $d_{k,t-j} = \{^1_0\}$ when $y_{t-j} \{^{\in S_k}_{\notin S_k}\}$, $k = 1, \ldots, K$, $j = 1, \ldots, m$. Depending on the value taken by the lagged variable y_{t-j}, this identifies K regimes $(S_1, \ldots, S_K)$ with the $d_{k,t-j}$'s being variables capturing the switching between regimes, $j = 1, \ldots, m$. When x_t includes the variables $d_{k,t-j}$'s, this allows the autoregression parameter $\beta_j(r, x_t)$ to vary across the K regimes, $j = 1, \ldots, m$. The general case corresponds to a threshold quantile autoregressive (TQAR[m]) model where, for each lag j, $\beta_j(r, x_t)$ can vary both across quantiles $r \in (0, 1)$ and across regimes (Galvao, Montes-Rojas, and Olmo 2011; Chavas and Di Falco 2017). When $\beta_j(r, x_t) = \beta_j(x_t)$, $j = 1, \ldots, m$ (i.e., when the autoregression parameters do not vary across quantiles), a TQAR(m) reduces to a threshold autoregressive (TAR[m]) model (see Tong 1990). And as noted above, a TQAR(m) model includes as special cases a QAR(m) model (obtained when $\beta_j(r, x_t) = \beta_j(r)$, $j = 1, \ldots, m$), as well as an AR(m) model (obtained when $\beta_j(r, x_t) = \beta_j$,

$j = 1, \ldots, m$). In general, a TQAR(m) model is very flexible at representing nonlinear dynamics. Indeed, in a TQAR(m) model and for each lag j, the autoregression parameter $\beta_j(r, x_t)$ can vary with the value of the current variable y_t (as captured by the quantile r), with the value of the lagged variable y_{t-j} (as captured by the regime-switching variables $d_{k,t-j}$'s), and with the value of other variables in x_t. A TQAR(m) model will be used below in our empirical investigation of dynamics.

Consider a sample of n observations on (y, X), where X is a vector of explanatory variables and $q(r \mid X) = X\beta(r)$, $r \in (0, 1)$. Denote the ith observation by (y_i, X_i), $i \in N \equiv \{1, \ldots, n\}$. For a given quantile $r \in (0, 1)$ and following Koenker (2005), the quantile regression estimate of $\beta(r)$ is

$$\hat{\beta}(r) \in argmin_{\beta}\{\sum_{i \in N} \rho_r(y_i - X_i\beta)\}, \tag{7}$$

where $\rho_r(w) = w[r - I(w < 0)]$ and $I(\cdot)$ is the indicator function. As discussed in Koenker (2005), the quantile estimator $\hat{\beta}(r)$ in equation (7) is a minimum-distance estimator with desirable statistical properties. The quantile estimator (7) applied to the dynamic specification (6) will provide the basis for our empirical analysis presented next.

8.4 An Application to the Dynamics of Wheat Productivity

Our investigation proceeds studying the dynamics of wheat productivity in Kansas. The analysis involves annual wheat yield in Kansas over the period 1885–2012 (USDA 2015). This covers the period of the American Dust Bowl (in the 1930s) when the US Great Plains were affected by a major environmental catastrophe. 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: (a) severe drought leading to crop failure and triggering massive migration out of the western Great Plains, and (b) soil and wind erosion (Hornbeck 2012). The Dust Bowl had short-term effects on agricultural production (as drought generated crop failure). But it also had longer effects: soil erosion had lasting adverse effects on land productivity (Hornbeck 2012). Kansas has been the leading wheat producing state in the United States (USDA 2015). As noted in the introduction, this makes studying wheat yield dynamics in Kansas a great case study of the response of productivity to environmental shocks.

The data on wheat yield (t / ha) in Kansas over the period 1885–2012 were obtained from the United States Department of Agriculture (USDA 2015). They are presented in figure 8.2. Figure 8.2 shows three interesting features. First, as expected, the early 1930s (corresponding to the Dust Bowl) is a period exhibiting low yields. Second, wheat yields have been trending upward, especially after 1940, indicating the presence of significant productivity growth and technological progress over the last seventy years. Third,

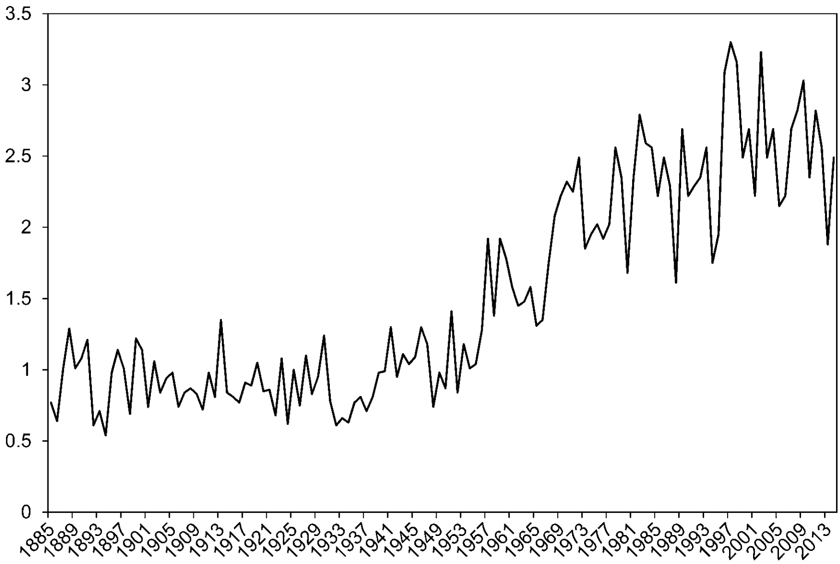

Fig. 8.2 Kansas wheat yield (ton per ha)

there is much variability in yield over time, reflecting the impact of various environmental shocks (including weather shocks).

Our investigation explores the distribution of wheat yield as if we were farmers. Since weather shocks are mostly unpredictable, it means that the distribution of yield is evaluated ex ante at the beginning of the growing season, that is, before weather shocks become observable. In the ex ante assessment, the yield distribution is thus *unconditional* with respect to *all* unobservable factors affecting farm productivity (including weather effects). In this context, the investigation of dynamic adjustments in Kansas wheat yield is presented next.

8.4.1 Preliminary Econometric Analysis

We start with a simple analysis of yield dynamics. With wheat yield y_t as the dependent variable, we first estimate simple autoregressive models. Table 8.1 presents the estimation results for alternative model specifications. Two time-trend variables are included in all models: a general time trend t = year – 2000 and a time trend t_1 = max {0, year – T_1} where t_1 captures technological progress after the year T_1. The models include autoregressive models of order m, AR(m), with $m = 1, 2$. Using a grid search, the value $T_1 = 1935$ was chosen as it provided the best fit to the data. 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(2) model is not statistically significant. A formal Wald test of the

Table 8.1 **Estimates of autoregressive models**

Parameters	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	0.0023***	0.024***	0.017**	0.017**
R^2	0.857	0.856	0.859	0.860

***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

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 8.1 also reports threshold autoregressive models (TAR[m]) allowing the autoregression parameters to vary across three regimes (d_i, d_2, d_3). The regimes are defined such that $d_{i,t} = \{^1_0\}$ when $y_t\{^{\in S_{i,t}}_{\notin S_{i,t}}\}$, $i = 1, 2, 3$, 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 reported in table 8.1. Thus, regime 1 means that yield is in the 1/3 lower quantile of the yield distribution, and regime 3 means that yield is in the 1/3 upper quantile of the yield distribution. In this context, having $d_{1,t-1} = 1$ corresponds to situations of low lag-1 yield where y_{t-1} is in regime 1. And having $d_{3,t-1} = 1$ corresponds to situations of high lag-1 yield where y_{t-1} is in regime 3. In TAR(m) models, the autoregression parameters are allowed to shift across the three regimes. For a TAR(1), table 8.1 shows that the lag-1 coefficient is 0.409 in regime 2, 0.507 in regime 1, and 0.407 in regime 3. Importantly, the difference in coefficients between regime 1 and regime 2 (0.098) is statistically significant at the 10 percent level. This provides statistical evidence that yield dynamics differ across regimes. This is our first hint of nonlinear dynamics. We also estimated a TAR(2) model. As reported in table 8.1, the lag-2 coefficients of the TAR(2) model are not statistically significant. A formal Wald test of the TAR(1) model as null hypothesis against a TAR(2) model gave a p-value of 0.959. Again, this indicates no significant dynamics going beyond one-period lag. On that basis, we continue our analysis based on autoregressive models of order 1.

Note that all estimated models reported in table 8.1 show that the overall time trend t is not statistically significant, but the effect of the post-1935

Table 8.2 **Estimates of threshold quantile autoregressive model TQAR(1) for selected quantiles**

	Quantile				
Parameters	$r = 0.1$	$r = 0.3$	$r = 0.5$	$r = 0.7$	$r = 0.9$
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.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

time trend t_1 is always positive and statistically significant. This reflects the presence of significant improvements in agricultural technology over the last seventy years.[3] Interestingly, the coefficient of the t_1 variable is smaller in the TAR(1) model (0.017) compared to the AR(1) model (0.023). This indicates that productivity growth interacts with changing dynamics across regimes.

8.4.2 Quantile Dynamics

Our preliminary analysis found statistical support for a TAR(1) specification. A discussed in section 8.3, while a TAR model allows the autoregression parameters to vary across regimes, it does not allow them to vary across quantiles of the current yield distribution. We now extend the analysis by considering a threshold quantile autoregressive model. As noted, a TQAR model provides a flexible representation of nonlinear dynamics by allowing autoregression parameters to change both across regimes and across quantiles. This section focuses on an ex ante analysis of quantile dynamics. An ex post quantile analysis (conditional on weather shocks) is presented in the next section.

Table 8.2 reports parameter estimates of a TQAR(1) model applied to wheat yield for selected quantiles (0.1, 0.3, 0.5, 0.7, 0.9). The variables are the same as in the TAR(1) model reported in table 8.1. Table 8.2 shows how the dynamics vary across quantiles. We tested the null hypothesis that the regression parameters are the same across quantiles (0.1, 0.5, 0.9). With 10 degrees of freedom, the chi-square test value was 5.703 with a p-value less

3. Note that technological progress involves many factors, including improved wheat varieties, increased use of fertilizer, greater reliance on irrigation, and improved farm management practices.

than 0.01. This implies a strong rejection of the TAR(1) model in favor of the TQAR(1) model. Thus, we find statistical evidence that the regression parameters vary across quantiles. Table 8.2 shows that the lag-1 coefficient under regime 2 is 0.687 at the 0.1 quantile. This coefficient is larger than for higher quantiles, indicating the presence of stronger dynamics in the lower tail of the yield distribution. Table 8.2 also reports that, for the 0.1 quantile, the lag-1 coefficient differs between regime 1 (where $d_{1,t-1} = 1$) and regime 2. The difference is 0.234. Using bootstrapping for hypothesis testing, we find this difference to be statistically significant at the 1 percent level. This provides evidence against a QAR model and in favor of a TQAR specification. 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 very different under repeated adverse shocks. As we show below, this is a scenario where adjustments also become qualitatively different.

In addition, table 8.2 shows the effects of the t_1 trend variable are much stronger in the upper tail of the distribution. This indicates that technological progress has contributed to a rapid increase in the upper tail of the yield distribution. But such effects are weaker in the lower tail of the distribution. This reflects significant shifts in the shape of the yield distribution over time (as further discussed below).

To conduct robustness checks, we explored issues related to the number of lags used in our dynamic analysis. While table 8.2 reports estimates for a TQAR(1) model, we also estimated a TQAR(2) model. In a way consistent with the results shown in table 8.1, we found that none of the lag-2 coefficients were statistically significant. This indicates that the TQAR(1) model provides an appropriate representation of dynamics. On that basis, the analysis presented in the rest of the chapter focuses on a model with one-period lag.

8.5 Implications

Our estimated TQAR(1) model provides a refined representation of the nonlinear dynamics of yield. As noted in section 8.3, it allows for flexible patterns of stability and instability. To explore in more detail the nature and implications of these patterns, we estimate our TQAR(1) model for *all* quantiles, thus providing a representation of the whole distribution of wheat yield and its dynamics.

First, we use our TQAR(1) model estimated for all quantiles to evaluate the distribution function of wheat yield at selected sample points. The resulting simulated distribution is presented in figure 8.3 for selected years (1950, 1970, 1990, 2010). As expected, over time, the distribution shifts strongly

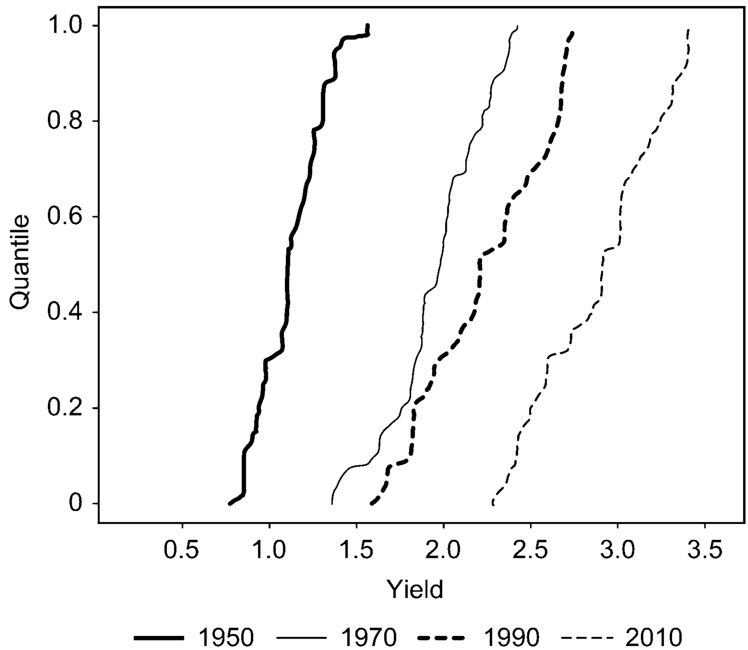

Fig. 8.3 Simulated yield distribution

to the right, reflecting the major effects of technological progress on agricultural productivity. Interestingly, the yield distribution exhibits greater spread (and thus greater risk exposure) in 2010 than in previous years, indicating an increase in the magnitude of unpredictable shocks (possibly due to climate change).

Next, 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. As discussed in section 8.2, dynamics is locally stable (unstable) at points where $\lambda < 1$ (> 1). We calculated the root λ for all quantiles and all three regimes. The results are reported in figure 8.4. Figure 8.4 documents the patterns of nonlinear dynamics associated with our estimated TQAR(1) model. It shows three important results. First, from figure 8.4, the root λ is similar across all three regimes for quantiles greater than 0.3, but it exhibits different dynamics for lower quantiles (less than 0.3). More specifically, compared to other regimes, the root λ is larger under regime 1 (when lagged yield is low) *and* in the lower tail of the distribution. This is consistent with the discussion of table 8.2 presented in the previous section.

Second, figure 8.4 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

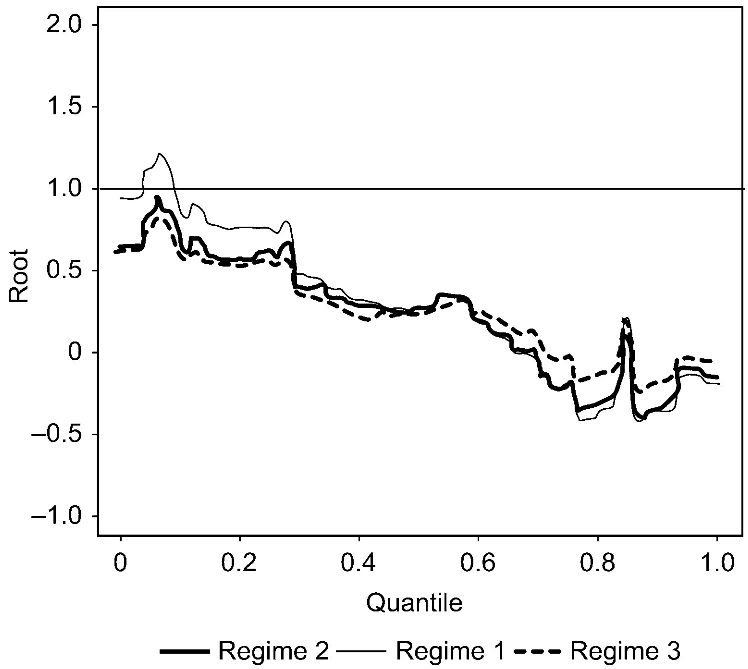

Fig. 8.4 Root of the dynamic yield equation

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. As discussed in section 8.2, this would preclude finding any evidence of traps.

Third, figure 8.4 shows that the root λ can be larger than 1 but only in situations of successive adverse shocks, that is, 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. This has several implications. First, we have identified a zone of local dynamic instability, that is, a zone of tipping points where the system tends to escape from. Second, associating a zone of instability with successive adverse shocks is an important finding. 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 in section 8.2, 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 8.1). 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 8.1).

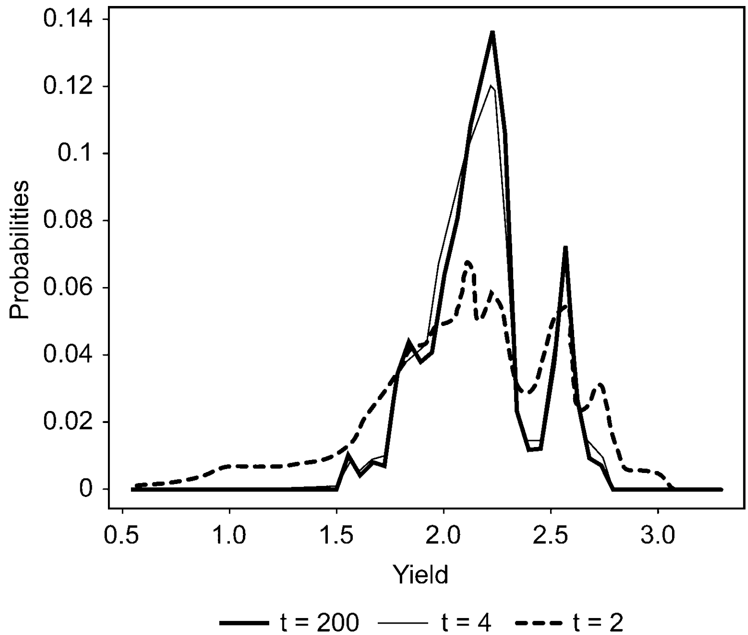

Fig. 8.5 Simulated probability function of wheat yield in the short run (*t* = 2), intermediate run (*t* = 4), and long run (*t* = 200)

In our case, 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. Thus, the zone of instability can be associated with a resilient system that tends to escape from low productivity toward higher productivity under adverse shocks. Indeed, figure 8.4 exhibits patterns that are similar to Scenario 3 in figure 8.1. To examine this issue in more detail, we consider the Markov chain representation of our TQAR(1) model, as given in equations (5a) and (5b). Using $K = 50$ and evaluated under conditions occurring in 1995, we obtained the Markov matrix A in equation (5b). The matrix A has a unique unit root, indicating that the Markov chain is stationary and has a long-run distribution. The second root of A has modulus 0.37, indicating a fairly fast adjustment toward the long-run distribution. The evolution of the probability function of wheat yield was simulated from equation (5b), starting from a uniform distribution over the range of the data. Starting at $t = 0$, the simulated probabilities are reported in figure 8.5 under three scenarios: in the short run (after 2 periods, $t = 2$), in the intermediate run (after 4 periods, $t = 4$), and in the long run (after 200 periods, $t = 200$). Figure 8.5 shows several important results. First, the adjustments toward the steady-state probability function occurs fairly quickly. Second, the simulated probability functions depart from the normal distribution in two ways: (a) they exhibit multiple peaks, and (b) they are skewed, with a left tail that is much longer than the right tail. Indeed, in all scenarios, Shapiro-Wilk tests of normality have a p-value less than 0.01, providing strong evidence of departure from normality. Third, figure 8.5 shows that the probability of being in the left tail of the probability function declines fast as one moves forward in time (as t goes from 2 to 4 to 200). This implies 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 figure 8.5 documents the presence of resilience. In other words, our estimated TQAR(1) model applied to wheat yield dynamics has two key characteristics: (a) a zone of instability occurs in the presence of successive unfavorable shocks, and (b) resilience arises as the underlying dynamic process tends to escape from this unfavorable zone. The significance of these findings is further discussed in section 8.8 below.

As discussed in section 8.2, the TQAR model reported in table 8.2 is a reduced-form model. While a reduced-form model provides a valid representation of dynamics, it does not provide structural information on the nature of dynamics. In the Kansas agroecosystem, a major source of shocks comes from the weather. Indeed, the Dust Bowl was the result of a major drought that hit the western Great Plains in the 1930s. This suggests evaluating a structural model where weather variables are explicit determinants of Kansas wheat yield. On that basis, we also specified and estimated a dynamic model of wheat yield including the effects of three weather variables: rainfall in the previous fall *rainf*, rainfall in the spring *rains*, and average temperature during the growing season *temp*. Data on these variables were obtained from Burnette, Stahle, and Mock (2010), Burnette and Stahle (2013), and the National Oceanographic and Atmospheric Administration (NOAA 2016).[4] These weather variables were introduced in the model both as intercept shifters and as interactions with lagged yield. These interaction effects allow yield dynamics to vary with weather conditions. Estimates of the associated quantile regression equation is presented in table 8A.1 in the appendix. As expected, table 8A.1 shows that weather has statistically significant effects on yield. Rainfall in the previous fall has a positive effect on yield, especially on the lower tail of the distribution. Temperature has a negative effect on yield through its interaction effect with lagged yield, especially in the upper tail of the distribution. This documents that both drought and high temperature have adverse effects on agricultural productivity. Such results are consistent with previous research (e.g., Tack Harri, and Coble 2012; Tack, Barkley, and Nalley 2015). Table 8A.1 also shows the presence of dynamics. Lagged yield has statistically significant effects on current yield either directly or through its interaction with temperature.

4. Rainfall is measured in millimeters and temperature in degree Celsius.

To evaluate the nature of dynamics in the structural model reported in table 8A.1, we calculated the root of the estimated dynamic process across quantiles. Interestingly, we found that the root varies between −0.2 and +0.6 depending on the evaluation point. The root is always in the unit circle for any quantile or any weather condition within the range of data. This implies global stability. Thus, the dynamic model reported in table 8A.1 does not show any evidence of instability. This contrasts with the reduced-form model reported in table 8.2 (which exhibits local instability as discussed above).[5] While this result is somewhat surprising, it has two important implications. First, since controlling for weather effects implies the disappearance of instability, it means that there is close association between instability and weather shocks. In other words, our reduced-form evidence of instability must be linked with weather shocks. Second, weather being mostly unpredictable, we do not expect much dynamics in the determination of weather shocks. This indicates that any linkage between weather and yield dynamics must be because of the dynamic response of management and policy to weather shocks. We expand on this interpretation below.

8.6 Discussion

From our reduced-form model, our first finding is about local dynamic instability arising, but only under unfavorable shocks. This is important. It suggests that a search for local instability is unlikely to be successful if the analysis focuses on "average conditions." This can be problematic in economic research to the extent that most econometric analyses involve estimating means or conditional means. While studying the properties of means and conditional means can be interesting, it neglects key information related to events located in the tails of the distribution. In a stochastic context, our findings indicate a need to expand analyses with a focus on dynamics associated with rare and unfavorable events. This is an intuitive argument. On the positive side, increasing resilience is about improving the odds of escaping the long-term effects of facing adverse shocks. On the negative side, avoiding collapse or traps is about reducing the odds of facing adverse conditions and increasing the odds of escaping toward better outcomes. All escape scenarios are about identifying local instability. Our TQAR model provides a good basis to support such inquiries.

Our second finding is also very interesting: applied to wheat yield dynamics, our analysis uncovered evidence of resilience as local instability tends to create an escape away from unfavorable events toward improved outcomes. But it also raises questions about the process supporting such dynamics. Below, we reflect on this process and the interpretations and implications of our findings.

5. Note that Chavas and Di Falco (2017) obtained a similar result for English wheat.

As noted above, our analysis has relied on an ex ante analysis of yield dynamics and focused on assessing the distribution of yield based on information available at the beginning of each growing season. Since weather conditions are mostly unpredictable, we treated the effects of rainfall and temperature during the growing season as part of the shocks represented by the yield distribution function. This raises the question: What constitutes an adverse shock? Much research has examined the determinants of wheat yield (e.g., Olmstead and Rhode 2011; Tack, Barkley, and Nalley 2015). Both rainfall and temperature are major factors affecting wheat yield (e.g., Tack, Barkley, and Nalley 2015; Chavas and Di Falco 2017). In particular, farming in the western Great Plains faces much rainfall uncertainty as it has experienced repeated periods of severe droughts (Burnette and Stahle 2013). One of the most severe droughts occurred in the 1930s: it led to 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.

First, 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 in reducing the incidence of wind erosion in the western Great Plains (Hurt 1981). The circumstances under which the SCS was created are of interest. Starting in 1932, severe droughts caused widespread crop failure in the Great Plains, exposing the soil to blowing winds and generating large dust storms. On March 6, 1935, and again on March 21, 1935, dust clouds passed over Washington, DC, and darkened the sky as Congress was having hearings on soil conservation legislation. It motivated policymakers to act: the Soil Conservation Act was signed by President Roosevelt on April 27, 1935, creating the Soil Conservation Service in the USDA. This was an example of a fast policy response to a crisis.

The Dust Bowl also stimulated significant adjustments in agricultural management. The SCS established demonstration projects to persuade farmers to adopt more sustainable tillage and cropping practices (including contour plowing, terracing, strip cropping, planting drought resistant crops, and greater reliance on pasture). For participating farmers, the SCS programs contributed to improving farm practices, increasing land values, and boosting farm income (Hurt 1981). As a result, farmers shifted land from wheat into hay and pasture, and they implemented new soil conservation techniques (Hornbeck 2012, 1480). Such changes helped mitigate the adverse effects of severe droughts.

Second, the Dust Bowl did not start a process of desertification of the western Great Plains. On the contrary, cultivated farmland increased during the 1930s and 1940s (Hornbeck 2012, 1480–90). This indicates that the 1930s droughts stimulated major innovations in agricultural management and policy. To the extent that these changes reduced the adverse effects of droughts, they contributed to creating a more resilient agroecological system.

Thus, we associate our evidence of resilience with induced innovations in both policy and management that followed the Dust Bowl. This interpretation raises the question: What would have been the effects of the Dust Bowl without such innovations? Of course, this is a hypothetical scenario that we have not observed, but we can discuss what might have happened. First, our evidence of resilience would likely disappear. For example, without innovations, continued soil erosion may have led to the desertification of the western Great Plains. Under this scenario, the adverse long-term effects of the Dust Bowl assessed by Hornbeck (2012) would have been much worse. The agroecosystem of the western Great Plains may have collapsed. In this case, the zone of instability identified in figure 8.4 would move to the right. In the context of figure 8.1, this would correspond to a move from Scenario 3 (resilience) toward Scenario 2 or even toward Scenario 4 (collapse). The process of collapse would occur when adverse shocks put the system in the zone of instability with a tendency to move toward lower outcomes (e.g., Scenario 4 in figure 8.1). Figure 8.5 would also change. Under collapse, the lower tail of the yield distribution would become much thicker. And the probability function may exhibit multiple peaks in the lower tail, with a new peak possibly rising in the extreme lower tail (corresponding to collapse). In this case, a key issue would be whether "valleys" exist in between peaks in the probability density function. The presence of valleys would indicate that there are positive probabilities of escaping the lower tail of the distribution. Alternatively, the absence of such valleys would mean any collapse obtained under adverse shocks would be irreversible.

Of course, these hypothetical scenarios differ from the ones reported in figures 8.4 and 8.5. Yet, our discussion has three 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. Our analysis indicates the important role played by the induced response of management and policy to adverse shocks.

8.7 Conclusion

This chapter has studied the dynamic response to shocks, with an application to agroecosystem productivity. It has proposed a threshold quantile autoregressive 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 finds 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. Our empirical analysis focused on a particular agro-ecosystem. Our findings documented the role of local instability in response adverse shocks. Such findings are expected to vary across situations. This motivates a need to extend our analysis and its applications to other economic systems where traps and resilience issues are of interest.

Appendix

Table 8A.1 Estimates of quantile autoregressive model of wheat yield including weather shocks, selected quantiles

	Quantile				
Parameters	$r = 0.1$	$r = 0.3$	$r = 0.5$	$r = 0.7$	$r = 0.9$
Intercept	0.44929	0.02457	0.11511	−0.09011	−0.06440
y_{t-1}	0.22780	0.23496	0.29597**	0.18766	0.19131**
rain_s	−0.00045	−0.00043	0.00055	0.00027	0.00025
rain_f	0.00094*	0.00071	0.00089	0.00119**	0.00074
temp	−0.00081	0.00994	0.00584	0.01346	0.01549
rain_s * y_{t-1}	0.00057	0.00060	−0.00068	−0.00040	−0.00036
temp * y_{t-1}	−0.00395	−0.01454	−0.01458	−0.02326***	−0.02495***
t	−0.00076	−0.00108	−0.00356	−0.00520**	−0.00093
t_1	0.01823***	0.02043***	0.02751***	0.03565***	0.03070***

Note: Hypothesis testing is conducted using bootstrapping.
***Significant at the 1 percent level.
**Significant at the 5 percent level.
*Significant at the 10 percent level.

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