# The Use of Nonstationary Panel Time Series Data in the Analysis of Farmland Values *

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**Abstract**

Time-series methods based on panel data are used to increase the power of conventional econometric tests of present value models commonly applied to studies of asset valuation. A second contribution is to allow for the presence of frictions in farmland markets by allowing for threshold nonlinearities in the empirical model. Using county-level data on Iowa farmland prices and cash rental rates between 1987 and 2010, panel data unit root models that allow for switching-regimes provide evidence in favor of the present value models. In one regime, where a threshold in the spread between rents and values is yet to be reached, deviations are persistent and contribute to drive land prices away from their intrinsic values. Conversely, the other regime is characterized by strong mean reversion in which market valuation becomes closer to fundamental determinants of values.

## 1 Introduction and Literature Review

Farm real estate, including land and buildings, is a critical asset in the agricultural sector, accounting for nearly 84 percent of total U.S. farm assets in 2009. It is the main investment item for a typical farm and a principal source of collateral for farm loans, enabling farm operators to finance the purchase of additional farmland and equipment or to finance current operating expenses.

Boom-boost cycles in farmland prices trigger noticeable wealth changes in the farm sector as farmland is the most important asset in the sector. Farmland values rose throughout much of the post-World War II period, and from 1969 to 1978, farmland prices increased 73 percent as farmers responded to high returns and various federal policies that increased incentives for investing in agriculture. In 1980, farmland prices began to decline in response to federal monetary policy that raised interest rates to help resolve high inflation. In addition to rapidly rising interest rates, higher energy prices contributed to a significant financial crisis in the farm sector during the 1980s that led to farm bankruptcies and bank failures.

Since the farm crisis of the mid-1980s, farmland real estate values have been rising in both nominal and real terms.[1] Between 1994 and 2004, real values increased between 2 and

[1] Figure 1 illustrates historical levels of nominal and real farmland values in Iowa, one of the major corn and soybean producing states.

4 percent annually, and in 2005 and 2006 experienced sharp annual increases of 16 percent and 11 percent respectively, before slowing to 7 percent and 6 percent annual growth in 2007 and 2008. Despite a 35 percent drop in farm income in 2009, U.S. farmland values rose slightly based on the potential for increased profits in 2010 (USDA/NASS, Land Values and Cash Rents summary, 2010). The value of farmland in the 48 continental states averaged $2,140 per acre at the beginning of 2010, 1.4 percent higher than the value in 2009.

Meanwhile, cash rents paid to landlords for cropland in 2010 rose $3 per acre, or 3 percent, nationwide. Renting farmland is a common practice in U.S. agriculture. Nationwide, about 45 percent of farmland is leased by operators. This percentage is even larger in major crop regions such as the Corn Belt. The major corn and soybean producing states of Illinois, Indiana and Iowa experienced increases in cropland cash rents in 2010. Cash rents in Illinois increased 3.7 percent to $169 per acre, while cash rents in Indiana and Iowa increased approximately 1 percent to $141 and $176 per acre, respectively.[2] The increase in cropland rental rates are considered to be the result of producers receiving strong commodity prices, while pasture cash rents seem affected less by commodity prices and more by land values (USDA/NASS, 2011).

Recently, increasing farmland values have generated considerable attention and have given rise to questions about the factors driving farmland values and whether current farmland values are 'reasonable' and sustainable. A common approach to valuing farmland is based on a net-present value model (PVM). Farmland is a capital asset that produces earnings indefinitely into the future. For this reason, the value placed on farmland should reflect the market's consensus of the present value of those future returns. The traditional income capitalization model provides a straightforward approach with which to view the economic fundamentals of farmland values. This model simplifies the farmland valuation problem and expresses current farmland values as a function of current income produced by farmland, the opportunity cost of capital or discount rate, and the rate at which income is expected to grow in the future.

[2] Figure 2 compares historical levels of nominal cash rents and farmland values in Iowa.

The present value of an acre of land is modeled as the sum of expected future cash flows derived from the land, discounted according to the risk of individual sources of these cash flows. The empirical model is based on the following assumption (Campbell and Shiller 1988a; Falk 1991): The present value model of real land prices requires that, if the real cash rents posses a unit root, then so must the price of land itself. Furthermore, land prices and cash rents must be moving together in the long-run. Assuming a fixed, constant discount rate, they must be cointegrated with a unit coefficient on rents to assure that variations in (logarithmic) cash rents-to-price ratios (i.e., the spread) reflect only temporary deviations from the their mean value. However, there has been a divergence between farmland values and returns to land from agriculture. Market prices of land have increased significantly over the past two decades, while there has been much less of an increase in the cash flow generated from farmland.

Falk (1991) is among the first who tests efficient market hypothesis for farmland markets with the present value model. Following the work of Campbell and Shiller (1987), Falk (1991) tests the present value model assuming a constant discount rate using annual Iowa farmland values and returns between 1921 and 1986. He rejects the null hypothesis finding that farmland markets are not efficient. Similarly, Falk (1992) tests the farmland market efficiency with a time-varying discount rate using vector autoregressions and rejects the null hypothesis. He suggests that fundamental changes in the market, such as changes in the tax codes, are the reason for the lack of efficiency in farmland markets.

Later, Falk and Lee (1998) decompose changes in farmland prices into three components, a permanent fundamental component, a temporary fundamental component, and a non-fundamental component, in order to study differences in explanations of farmland prices. Fundamental components are defined as shocks that influence the time path of rents and the time paths of interest rates. Examples of these shocks are government policy, weather and technology breakthroughs, and these shocks can be permanent or temporary. Non-fundamental components are shocks that influence the farmland prices, but not the paths of rent or interest rates. These shocks are viewed as overreactions by the market, and they are not associated with any known fundamental changes. Falk and Lee (1998) conclude that farmland values are inefficient due to a combination of temporary fundamental factors and non-fundamental factors. Similar results are reported for Illinois by Clark, Fulton, and Scott (1993).

Tegene and Kuchler (1993) later find that speculative bubbles do not occur in farmland markets. Using cointegration, the authors accept the notion that market fundamentals are a determinant in the movement of farmland values. Engsted (1998) contradicts Tegene and Kuchler's (1993) findings and argues that cointegration is not useful when examining discount rates and expectations in the PVM. He notes that cointegration tests do not provide evidence to whether expectations are "backward looking" or "forward looking" nor evidence to whether the discount rate is constant or time-varying. Engsted (1998) uses the same data set and vector autoregressions (VAR) for the empirical analysis and rejects the null hypothesis of market efficiency. He notes that present value models should be tested assuming time-varying discount rates as suggested by Falk (1992). In general, these studies find evidence of divergence between the present value of future cash flows and the market price of farmland, and they suggest that other factors beyond returns from agriculture may play a role in determining land values.

One possible explanation for the lack of consensus about farmland pricing and the explanatory power of the PVM might be the presence of market frictions. Market frictions, including transactions costs and the large capital investments necessary to participate in the agricultural land markets, may cause nonlinearities in the adjustment of land values and cash rents towards their long run equilibrium. Transactions costs may drive a wedge between the price at which outsiders wish to buy land and that at which farmers wish to sell it. The market price can be anywhere within this wedge, and can easily deviate from its frictionless present value. One can interpret this wedge as a band of inaction inside which farmers neither buy nor sell land, even in the face of changing expected returns. Such a band would be centered on the price that would prevail in the absence of transactions costs, and its width would be determined by the size of these costs. Although the costs associated with trading many financial assets are small, costs involved in transferring ownership of farmland typically exceed $7-8$ percent of the purchase price (de Fontnouvelle and Lence 2002). Large transactions costs might be in effect not only when buying/selling farmland, but also in rental markets of farmland. In particular, rental agreements in agricultural land markets may be relatively fixed in the short run; and thus, significant transactions costs may be associated with the re-negotiation of rental contracts.

Just and Miranowski (1993) are the first to explicitly incorporate the potentially large transactions costs involved in the transfer of ownership of farmland. They develop a structural model of farmland prices that explicitly accounts for a large number of relevant issues, such as the "multidimensional effects of inflation associated with capital erosion, savings-return erosion, and real debt reduction as well as the effect of changes in the opportunity cost of capital" (Just and Miranowski 1993; p. 168). However, they do not test whether transactions costs are the reason behind the lack of support for the PVM. Chavas and Thomas (1999) introduce a dynamic theoretical model of land prices, allowing for non-additive dynamic preferences and risk aversion, as well as transaction costs. Chavas and Thomas (1999) perform Generalized Method of Moments analysis of U.S. land values for the period 1950-1996. Their findings indicate that transactions costs have significant effects on land prices.

Lence (2001) argues that both studies mentioned above fail to recognize the non-stationary nature of farmland prices. Lence and Miller (1999) analyze farmland prices in the presence of proportional transactions costs while restricting their attention to the widely-applied constant-discount rate version of present value model (CDR-PVM). They re-formulate the CDR-PVM accounting for the frictions created by transactions costs. Their empirical analysis is based on an autoregressive model of the stochastic discounted excess return. Using Iowa data for the period of 1900-1994, they find mixed evidence regarding the CDR-PVM in the presence of transactions costs. The CDR-PVM was consistent with typical transactions costs assuming a one-period holding horizon, but not when an infinite-holding horizon was hypothesized. de Fontnouvelle and Lence (2002) use kernel regressions to test the theoretical model of Lence and Miller (1999). They also expand Lence and Miller's (1999) data set to include 20 major agricultural states between 1921 and 1990, as well as two different national series. They confirm that the behavior of land values and rents is consistent with the CDR-PVM in the presence of typical transactions costs such as sales commissions and other fees. Finally, Lence (2003) tests the model developed in Lence and Miller (1999) using a threshold autoregressive model (TAR) rather than a standard one. Using Iowa farmland data over the period of 1900-1994, Lence (2003) argues that a TAR model gives a better representation of farmland-pricing behavior. He finds that the behavior of land prices is consistent with the necessary conditions for market equilibrium under rational expectations and the typical transactions costs observed in land markets.

Another possible explanation for the absence of empirical support for the present value model might be that standard econometric tests may not be powerful enough to detect long run equilibrium when applied to single time series. A promising approach would be to combine the sample information from the time series dimension with that from the cross-section. Panel data methods are expected to be more powerful than conventional methods based on single time series. Gutierrez, Westerlund, and Erickson (2007) use a panel-time series framework to test for the present value model of the U.S. farmland. They argue that the failure to find cointegration between farmland prices and cash rents may be due to the low power of their tests and to the presence of structural changes representing a shifting risk premium on farmland investments. They use panel unit root and cointegration tests that allow for breaks in the cointegration relationship. Their empirical results, based on a panel covering 31 U.S. states between 1960 and 2000, suggest that the present value model of farmland prices cannot be rejected once accounted for the structural change in early 1980s.

The objective of this essay is to explore whether the absence of empirical support for the present value model can be attributed to the restrictiveness of conventional time series methods. Two potential pitfalls are addressed: First, a larger panel data set is used instead of a single univariate time series to gain more power in unit root testing. Second, the potential for nonlinearities in the adjustment process is investigated. In particular, the objective is to analyze panel data comprised of logarithmic ratios of cash rents to farmland prices in order to test for the implications of the conventional present value models. Significant cross-sectional correlation among time series in such panels is addressed, and a factor model is employed to account for this correlation. Then, the analysis focuses on a decomposition of the panel into its common and idiosyncratic components to answer the following questions. First, are the observed data stationary, and if the data are nonstationary, is it because of nonstationary common components or nonstationary idiosyncratic components? Second, how many common factors are necessary to capture the cross-sectional correlations and how many of these common factors are nonstationary? Third, do the estimated factors represent some observable variables of interest? And, finally, is there a possibility that the common factors are (stationary) threshold autoregressive processes rather than pure unit root processes? In this last step, nonstationarity of the common factor is further investigated by allowing for the possibility of a nonlinear, piece-wise stationary autoregressive process in the estimated common factor. To this extent, threshold nonlinearity is assumed to be in effect in the estimated common factor of the Iowa farmland markets, where the transactions costs may create a threshold which limits adjustment in the case of shocks that are too small to imply adjustments back to steady-state levels of the spread.

For the empirical analysis, a large, county-level panel data set made up of Iowa farmland prices and cropland cash rental rates is used. The data set is provided by Iowa State University. The data span different years for each of the 99 counties some of which are too short for implementing the panel unit root methods. Therefore, only counties that have data from 1987 forward are included in the analysis. This restriction is helpful in terms of having a homogeneous panel with the same start date for all counties, which in practice makes the econometric methods considered in the essay easier to implement. Iowa farmland data is used quite frequently in empirical studies of farmland valuation because of the following appealing features: First, farmland in the Midwest, especially in Iowa, is more homogeneous than farmland in other areas of the country; this is a characteristic that is especially looked for in panel data applications. Second, land in Iowa is not typically valued for its potential non-agricultural uses as is land in more urban states. Although time-series data on Iowa farmland have been used in other empirical studies of farmland valuation (see, among others, Falk; 1991, and Lence and Miller; 1999), I am not aware of any studies utilizing this particular panel data set.

The remaining of the paper is organized as follows. Section 2 summarizes the conceptual model which is based on the present value models introduced by Campbell and Shiller (1987). Section 3 gives an overview of the econometric methods used in the empirical analyses including methods that are specific to use of panel data and methods that allow for threshold nonlinearities in the model. Section 4 introduces the panel data set used in the analysis and reports empirical findings. The final section concludes and gives a direction for future research on the subject.

# 2 Theoretical Model

The theoretical framework is based on the simple present value model (PVM), which is central to most of the studies on farmland values. The present value of an asset is derived from its earning power, or the ability to generate future income. The present value theory suggests that there is a special relationship tying asset prices and returns together, such that movements in returns are mirrored by prices in the long run (Lloyd 1994). Although the present value of an asset is capable of reflecting its true value, it involves expectations of future income and the discount rates. Therefore, the predictions from present value models may not always be easy to test in practice. Linking the present value of an asset to its future income in the framework of integration and cointegration analyses, as proposed by Campbell and Shiller (1987), provides a useful tool for testing expectations and rationality in asset markets.

## 2.1 The Basic Present Value Model and its Time Series Characteristics

Let $P_{i,t}$ be the real price per acre of farmland in location $i = 1, ..., N$ at period $t = 1, ..., T$, and $C_{i,t+1}$ be the real rent per acre of farmland at the beginning of time $t+1$ derived from possessing the farmland between time $t$ and time $t+1$. Assuming the existence of riskless investment alternatives (i.e., bonds available in zero net supply with one period net interest rate, $R_i$), no arbitrage in land markets implies

$$E_t(P_{i,t}) = \frac{1}{1+R_i} E_t(P_{i,t+1} + C_{i,t+1}) \tag{1}$$

Equation 1 is the starting point of most empirical asset pricing tests. This first degree difference equation can be iterated forward to reveal the solution

$$P_{i,t} = \sum_{m=1}^{\infty} \frac{1}{(1+R_i)^m} E_t(C_{i,t+m}) + B_{i,t} \tag{2}$$

such that

$$E_t(B_{i,t+1}) = (1+R_i)B_{i,t} \tag{3}$$

The farmland price has two components; a 'market fundamental' part, which is the discounted value of expected future cash rents, the first term on the right-hand side of equation 2, and a 'rational bubble' part, the second term. In this setup, the rational bubble is not a mispricing effect but a basic component of the farmland price. Despite the potential presence of a bubble, there are no arbitrage opportunities –equation 3 rules these out.

Under the assumption that cash rents grow slower than $R_i$, the market fundamental part of the farmland price converges. The bubble part, in contrast, does not converge. The price may exceed its fundamental value as long as agents expect that they can sell the land at an even higher price at a future date. The expectation of making high capital gains from the sale of the farmland in the future is consistent with no-arbitrage pricing as the value of the right to sell the land is priced in. Importantly, the path of the bubble (and consequently the farmland price) is not unique. Equation 3 only restricts the law of motion for the non-fundamental part of the land price; however, it implies a different path for each possible value of the initial level of the bubble. Therefore, an additional assumption about $B_{i,t}$ is required to determine the price. A special case of the solution that pins down the price of farmland is $B_{i,t} = 0$, which implies that the value of the bubble is zero at all times. This is the fundamental solution that forms the basis of present value pricing approaches to asset prices.

Other than the absence of rational bubbles that are embedded in the present value model, the following assumptions are also required for the PVM solution:

- There are no informational asymmetries. Price movements are not driven by uninformed traders who try to extract information from prices.

- Agents are risk neutral. A corollary of this assumption is that there are no risk premium. This rules out time-varying risk premium due to variation in the price.

- The discount rates, $R_i$, are constant over time. If the discount rate is constant at $R_i$ and cash rents grow at the constant rate $g$, the $R_i$ must be greater than $g$ for the sum of the discounted stream of cash rents to be finite.

- The process that generates cash rents is not expected to change over time. Although this is not necessarily an assumption about the theoretical model, it is an assumption commonly made in the econometric tests of this model. Most econometric tests based on time series often need to generate an estimate of expected cash rents based on history. This exercise is meaningful only if the process generating cash rents is not expected to change in the future.

The present value model with the market fundamentals is a special case of a more general model that allows for bubbles. The no-bubbles special case is justified by a transversality condition in infinite horizon models. The price of the farmland today is the sum of the net present value of expected cash rents and the expected resale value of land:

$$P_{i,t} = \sum_{m=1}^{\infty} \frac{1}{(1+R_i)^m} E_t(C_{i,t+m}) + \lim_{m \to \infty} \left( \frac{1}{1+R_i} \right)^m P_{i,t+m} \tag{4}$$

The transversality condition asserts that the second term on the right-hand side of equation 4 is zero. This is justified by the following argument. If there is a positive bubble and this term is not zero, then infinitely-lived agent could sell the land and the lost utility, which is the discounted value of the stream of cash rents, will be lower than the sale value. This cannot be an equilibrium price as all agents will want to sell their land at such a price.

A useful variable to look at in present value models is spread, $S_{i,t}$. Imposing transversality condition and subtracting $P_{i,t}/(1+R_i)$ from both sides of equation 4 yields

$$P_{i,t} - \frac{P_{i,t}}{1+R_i} = \sum_{m=1}^{\infty} \frac{1}{(1+R_i)^m} E_t(C_{i,t+m}) - \sum_{m=1}^{\infty} \frac{1}{(1+R_i)^m} E_t(C_{i,t+m-1}) + \frac{C_{i,t}}{1+R_i} \tag{5}$$

Rearranging equation 5 gives

$$P_{i,t} - \frac{C_{i,t}}{R_i} = \left( \frac{1+R_i}{R_i} \right) \sum_{m=1}^{\infty} \frac{1}{(1+R_i)^m} E_t(\Delta C_{i,t+m}) \tag{6}$$

Equation 6 states that if $P_{i,t}$ and $C_{i,t}$ are both integrated of order 1, $I(1)$, series, then the two series are cointegrated with a cointegrating vector, $1/R_i$. Campbell and Shiller (1987) define $P_{i,t} - C_{i,t}/R_i$ as the spread, $S_{i,t}$. Spread links a stock variable, $P_{i,t}$, to a flow variable, $C_{i,t}$. If cash rents are constant over time, then the value of land is simply the current flow of cash rents divided by the rate of return, that is, the spread is zero. Otherwise, the spread is a function of the expected changes in future cash rents discounted. A positive spread reflects an overall growth in expected future cash rents, whereas a negative spread is associated with decrease in expected future cash rents generated by farmland.

## 2.2 Present Value Model with Approximate Time-Varying Expected Returns

Allowing for time-varying discount rates slightly complicates the analytical model compared to the case of a constant discount rate since the relationship between prices and returns turns out to be nonlinear. Campbell and Shiller (1988a) propose a log-linear approximation of the present value framework which enables investigating the behavior of stock prices under time-varying discount rates. The Campbell-Shiller version of the present value model relates $P_{it}$, the real price per acre of farmland in state $i = 1, ..., N$ in period $t = 1, ..., T$, to $C_{i,t+1}$, the real cash rent per acre of farmland paid at the beginning of $t+1$ for the land held from the beginning of time $t$ to the beginning of time $t+1$. Using this notation, the log of the gross real rate of return on an acre of land in state $i$ from period $t$ to $t+1$, $R_{i,t+1}$, can be defined as

$$\log(R_{i,t+1}) = \log\left(\frac{P_{i,t+1} + C_{i,t+1}}{P_{i,t}}\right) \tag{7}$$

or equivalently

$$\begin{aligned}\log(R_{i,t+1}) &= \log\left(\frac{P_{i,t+1} + C_{i,t+1}}{P_{i,t}}\right) \\ &= \log\left(\frac{P_{i,t+1}}{P_{i,t}}\right) + \log\left(1 + \frac{C_{i,t+1}}{P_{i,t+1}}\right) \\ &= \log(P_{i,t+1}) - \log(P_{i,t}) + \log(1 + \exp(c_{i,t+1} - p_{i,t+1})\end{aligned} \tag{8}$$

Therefore;

$$r_{i,t+1} = \log(1 + \exp(s_{i,t+1})) + p_{i,t+1} - p_{i,t} \tag{9}$$

where the lowercase letters represent the natural logarithms of the corresponding uppercase variables, and $s_{i,t+1} = c_{i,t+1} - p_{i,t+1}$ is the log of the ratio of cash rents to prices, usually referred to as the *spread* in the finance literature. The objective here is to write log-returns as a linear function of log-prices and log of cash rents, which is complicated by the first term on the right-hand side of equation 9. Campbell and Shiller (1988a) show that this problem can be solved by linearizing $\log(1 + \exp(s_{i,t+1}))$ around the time series mean of $s_{i,t+1}$, $s_i$ . Then, Equation 9 approximately equals to

$$r_{i,t+1} \approx k_i + s_{i,t} - \rho_i s_{i,t+1} + \Delta c_{i,t+1} \quad (10)$$

where $k_i = -\log(\rho_i) - (1 - \rho_i)\log(1/\rho_i - 1)$ and $\rho_i = 1/(1 + \exp(s_i))$ are parameters of linearization.

Equation 10 is essentially a difference equation, which can be solved forward indefinitely to obtain the following approximation for $s_{i,t}$:

$$s_{i,t} \approx -k_i/(1 - \rho_i) - \sum_{m=0}^{\infty} \rho_i^m (\Delta c_{i,t+1+m} - r_{i,t+1+m}) + \lim_{m \to \infty} \rho_i^m s_{i,t+m} \quad (11)$$

After taking expectations conditional on the information available at time $t$ and imposing the transversality condition (i.e., expected value of the last term on the right-hand side of equation 11 is zero), equation 11 can be re-written as

$$s_{i,t} \approx -k_i/(1 - \rho_i) + E_t \left[ \sum_{m=0}^{\infty} \rho_i^m (-\Delta c_{i,t+1+m} + r_{i,t+1+m}) \right] \quad (12)$$

Equation 12 expresses the current value of $s_{i,t}$ in terms of the present discounted value of expected future values of $\Delta c_{i,t+1}$ and $r_{i,t+1}$ . If changes in the log of cash rents and the log of discount rates follow a stationary process, log of land prices and log of cash rents are cointegrated with the cointegrating vector $[1, -1]$, and the log cash rents-to-value ratio (spread) is a stationary process. This cointegration relationship implies that if current land values are higher than current cash rents (i.e. investors are willing to pay more or the land is overpriced), cash rents are expected to grow in the future. If agents are fully rational under the present value model, then land prices and cash rents generated from land cannot drift arbitrarily and persistently far apart, thus the spread will show a reverting behavior towards an attractor.

A natural way to approach the empirical problem of testing for present value models is to test for a cointegration relationship between log-prices and the log of cash rents. However, cointegration and error correction models are complicated when considering nonlinear behavior and nonstationary panel data simultaneously. Complication arises from the need to estimate a long-run cointegrating vector and make inference on it. Instead of multivariate cointegration procedures, univariate unit root procedures can be utilized since the theoretical model at hand allows doing so. Equation 12 implies that the stationarity of the spread can be viewed as a necessary condition for the validity of the present value model. Therefore, the empirical analysis is based on testing the stationarity of the log of the cash rents-to-value ratio in a panel data framework.

Using a single variable for the testing problem has two main advantages in practice. The empirical investigation of the log of cash rents-to-value, first, does not involve estimating an unknown cointegrating parameter. Second, measurement problems associated with deflating nominal land prices and cash rents by some price index can be avoided. Working with natural logarithms of cash rents and prices instead of the levels of those variables is consistent with relaxing the assumption of constant expected returns in favor of (approximate) time-varying expected returns. Furthermore, with the exception of highly persistent expected returns and small samples, cointegration tests on the *log* of cash rents-to-value ratio tend to reject the null hypothesis of no-cointegration more frequently than those on the ratio of *levels* of cash rents and price series (Bohl and Siklos 2004).

# 3 Methodological Overview

This section surveys various econometric procedures that are used in the following section to analyze a panel data set on spread, and to answer the main questions raised in the introduction section. Mainly, two strands of econometric frameworks are utilized in the empirical analyses. The first one focuses on the use of panel data. If the sample size in a single time series is small and if the same data are available across a cross-section of units, then panel unit root tests might help obtaining a more precise and straightforward inference about the existence of unit roots by combining information from the time series dimension with that obtained from the cross-sectional dimension.[3]

The second strand of econometrics investigates the nonlinear dynamics of economic time series. It is widely recognized in recent literature that the conventional unit root tests, which are based on linear autoregressive models, may lack power to reject the null hypothesis of nonstationarity when the underlying process is nonlinear but stationary. This fact has raised interest in nesting unit root tests within various nonlinear dynamic frameworks.[4] The Self Exciting Threshold Autoregressive (SETAR) models, which are a particular class of nonlinear autoregressions, are used in this essay.

## 3.1 Unit Roots in Panel Data

Since Quah (1994) opened the door to the panel unit root testing literature, several important theoretical developments have been made by several researchers. Levin, Lin, and Chu (2002) generalize Quah's (1994) panel unit root test under the alternative of a homogenous panel. Im, Pesaran, and Shin (2003), Choi (2001) and Maddala and Wu (1999) consider panel unit root tests under the alternative of a heterogeneous panel. Along with the theoretical development of panel unit root tests, their use in empirical research has grown exponentially. The most important reason for their use is that panel unit root tests reject the null hypothesis of a panel unit root more often than univariate unit root tests. This is an expected result considering that the goal of panel unit root tests under the null hypothesis of a panel unit root is to amplify the power of tests through the pooling of information across units.

[3] See Breitung and Pesaran (2008) and Choi (2006) for recent surveys on panel unit root and cointegration methods.

[4] Unit root tests under structural breaks by Perron (1989), Zivot and Andrews (1992), Lumsdaine and Papell (1997), threshold autoregressive models by Enders and Granger (1998), Caner and Hansen (2001), Kapetanios and Shin (2006) and Seo (2008), smooth transition autoregressive models by Kapetanios, Shin, and Snell (2003) are examples of such tests among others.

However, the so called *first generation* panel unit root tests are based on the rather restrictive assumption of independence across cross-section units. The power of panel unit root tests suffers from serious size distortions when a panel is contaminated by cross-section dependence (O'Connell 1998). Often, economic theory dictates that it is not appropriate to assume that the cross section units are independent of each other. To relax this assumption, *second generation* panel unit root tests are developed to allow for different forms of cross-sectional dependence. Within this second generation of tests, the common factor structure approach is widely applied as a way of dealing with cross-sectional dependence. Phillips and Sul (2007), and Moon and Perron (2004) propose panel unit root tests under cross-sectional dependence which arises from unknown common factors. Their tests require elimination of the unknown common factors. Bai and Ng (2004) propose an effective de-factoring method. Bai and Ng (2004) go beyond this to analyze the source of nonstationarity. In this essay, the common factor approach suggested by Bai and Ng (2004) is used to account for cross-section dependence among Iowa counties.

### 3.1.1 Unit Root Tests for Independent Panels

Assume that the time series $\{y_{i,0}, \ldots, y_{i,T}\}$ on the cross-section units $i = 1, 2, \ldots, N$ are generated for each $i$ by an autoregressive process. Then, the basis for a panel unit root model can be written as the univariate augmented Dickey-Fuller (ADF) regression:

$$\Delta y_{i,t} = \alpha_i + \rho_i y_{i,t-1} + \sum_{j=1}^{k_i} \gamma_i \Delta y_{i,t-j} + \varepsilon_{i,t} \tag{13}$$

or

$$\Delta y_{i,t} = \alpha_i + \beta_i t + \rho_i y_{i,t-1} + \sum_{j=1}^{k_i} \gamma_i \Delta y_{i,t-j} + \varepsilon_{i,t} \tag{14}$$

where the errors $\varepsilon_{i,t}$ are identically and independently distributed (*i.i.d.*) across $i$ and $t$ with $E(\varepsilon_{i,t}) = 0$, $E(\varepsilon_{it}^2) = \sigma_{it}^2 < \infty$, and $E(\varepsilon_{it}^4) < \infty$. The null hypothesis states that all time series are independent random walks.

$$H_0 : \rho_i = 0 \, for \, all \, i = \{1, 2, \ldots, N\} \tag{15}$$

Two alternative hypotheses that can be considered are

$$H_{1a} : \rho_1 = \ldots = \rho_N = \rho \quad and \quad \rho < 0 \tag{16}$$

$$H_{1b} : \rho_1 < 0 \ldots \rho_{N1} < 0 \quad for \quad N_1 < N \tag{17}$$

$H_{1a}$, is a *homogeneous alternative* where the autoregressive parameters are assumed to be identical for all cross-section units, $i$ (see, for example, Levin, Lin, and Chu (2002)). $H_{1b}$ assumes that $N_1$ of $N$ cross-section units are stationary with individual specific autoregressive coefficients. This is referred to as the *heterogeneous alternative* (see, for example, Im, Pesaran, and Shin (2003), Maddala and Wu (1999) and Choi (2001)). Different panel unit root tests can be developed depending on which of the two alternatives is being considered. The panel unit root tests motivated by the first alternative, $H_{1a}$, pool the observations across different cross-section units before calculating the test statistics. The panel unit root test statistics computed for testing the heterogeneous alternative, $H_{1b}$, are computed as (standardized) averages of the underlying individual cross-section unit test statistics (or a suitable transformation of them, such as rejection probabilities). The outcome from these two types of tests should be evaluated with caution, especially when the null of unit root is rejected. The inference on unit root is more of a general statement such as 'a significant fraction of the cross-section units is stationary'. Panel unit root tests usually do not provide explicit guidance as to the identity of the cross-section units that are stationary.

***Levin, Lin, Chu (LLC) Test***

One of the earliest unit root tests developed for panel data is that of Levin and Lin, and Chu (2002).[5] They allow for heterogeneity of individual deterministic effects (constants and/or

[5] Levin and Lin test appears in 1992 for the first time. In 1993, they generalize the model to allow for autocorrelation and heteroscedasticity. Their paper in 2002 (Levin, Lin, and Chu 2002) presents major results from ten-years worth of research.

linear time trends) and heterogeneous serial correlation structures of the error terms. They do, however, assume homogeneous first order autoregressive parameters. In this sense, the LLC test may be viewed as a type of pooled Dickey–Fuller (or ADF) test. It is applicable to small $T$ large $N$ panels. The LLC test is based on the following equation:

$$\Delta y_{i,t} = \alpha_{0i} + \alpha_{1i} t + \rho y_{i,t-1} + u_{i,t}$$

where $i = 1, 2, \ldots, N$ and $t = 1, 2, \ldots, T$. The unit–specific fixed effects are an important source of heterogeneity, since the autoregressive parameter is restricted to be homogeneous across all units of the panel. $u_{i,t}$ is assumed to be independently distributed across individuals and follow a stationary invertible ARMA process for each $i$, $u_{i,t} = \sum_{j=0}^{\infty} \theta_{i,j} u_{i,t-j} + \varepsilon_{i,t}$.

Referring to equation 13, LLC assume homogeneous autoregressive coefficients among individual cross-section units, i.e., $\rho_i = \rho$ for all $i$ , and test for the null hypothesis in equation 15 against the alternative in equation 16. In the case of *i.i.d.* disturbances and no individual-specific fixed effects; under the null, the panel regression unit root $t-$statistic, $t_\rho$, based on the common estimator, $\hat{\rho}$, converges to standard $N(0, 1)$. However, if there are individual-specific fixed effects, time trends, or serial correlation in the disturbances, the resulting test statistic is not centered at zero, resulting in substantial impact on the size of the unit root test. In this case, Levin, Lin, and Chu (2002) suggest using an adjusted $t-$statistic, $t^*_\rho$, that involves mean and variance adjustment parameters. These parameters are obtained through Monte Carlo simulations and can be found in Table 2 of Levin, Lin, and Chu (2002) for a given deterministic specification and time series dimension. LLC show that adjusted $t-$statistic, $t^*_\rho$, obeys the standard normal distribution, asymptotically.

### *The Im, Pesaran, Shin (IPS) Test*

The LLC test is restrictive in the sense that it requires $\rho$ to be homogeneous across $i$. Im, Pesaran, and Shin (2003) (IPS) allow for a heterogeneous coefficient of $y_{i,t-1}$ and propose an alternative testing procedure based on averaging individual unit root test statistics. Instead of pooling the data, IPS consider the mean of the ADF (or DF) statistics computed for each cross-section unit in the panel when the error term $\varepsilon_{it}$ is serially correlated, possibly with different serial correlation patterns across cross-section units, and $T$ and $N$ are sufficiently large. The assumption on the error terms, $\varepsilon_{it}$, is that $\varepsilon_{it} \sim N(0, \sigma_i^2)$. Let $t_{i,T}$ $(i = 1, 2, \ldots, N)$ denote the individual t-statistics for testing unit roots, and let $E(t_{i,T}) = \mu$ and $V(t_i, T) = \sigma^2$. The individual $t$-test is defined by

$$t_{i,T} = \frac{\hat{\rho}_i}{\sqrt{\sigma_i^2}}$$

Im, Pesaran, and Shin (2003) compute separate unit root tests for $N$ cross-section units and define their "$t-$bar" statistic as a simple average of the individual ADF statistics, $t_{iT}$, as

$$\bar{t} = \frac{1}{N} \sum t_{iT}$$

IPS assume that $t_{iT}$ are $i.i.d.$ and have finite mean and variance. Therefore, by the Lindeberg-Levy Central Limit Theorem (CLT), the standardized $t-$bar statistic, $W_{tbar}$, converges to a standard normal variate as $N \to \infty$ under the null hypothesis.

$$W_{tbar} = \sqrt{N} \left( \frac{\bar{t} - \frac{1}{N} \sum_{i=1}^{N} E(t_{i,T} | \rho_i = 0)}{\sqrt{\frac{1}{N} \sum_{i=1}^{N} Var(t_{i,T} | \rho_i = 0)}} \right) \tag{18}$$

The values of the mean, $E(t_{i,T})$, and the variance, $Var(t_i, T)$, used in calculating $W_{tbar}$ statistic have been computed via Monte Carlo methods for different values of $T$ and number of augmented lags ($p_i$), and have been tabulated by Im, Pesaran, and Shin (2003). The null hypothesis is given in equation 15, and the alternative hypothesis is given in equation 17 (i.e. a heterogeneous alternative).

Simulations show the importance of the correct choice of the underlying ADF regression order, especially when the panel contains deterministic time trends. When the disturbances in the dynamic panel are serially correlated, the size and power of the $t-$bar test are reasonably satisfactory, however $T$ and $N$ have to be sufficiently large. In such a case, it is also critical not to underestimate the augmented terms of the underlying ADF regressions.

***Fisher Type Tests (Maddala-Wu (1999) and Choi (2001) )***

Maddala and Wu (1999) and Choi (2001) consider the shortcomings of both LLC and IPS frameworks and offer an alternative testing strategy. They suggest using a non-parametric, Fisher-type test statistic that is based on a combination of the $p-$values of the unit root test statistics for individual cross-section units. Both IPS and Fisher tests combine information based on individual autoregressive models and relax the restrictive assumption of the LLC test that $\rho_i = \rho$ under the alternative. However, Fisher type tests are built under more general assumptions than LLC or IPS tests. In fact, as Choi (2001) notes, earlier tests lack flexibility which might restrict their use in empirical applications. Specifically, they all assume the cross-section units to have the same type of non-stochastic components and $T$.

Choi (2001) proposes a simple test based on combining $p-$values from a unit root test applied to each unit of the panel data. There exists a number of possible ways to combine $p-$values. Assuming $pval_i$ is the $p-$value of a unit root test statistic on cross-section $i$, Fisher-type panel unit root test statistic proposed by Maddala and Wu (1999) can be written as

$$P = -2 \sum In(pval_i) \tag{19}$$

Under the null hypothesis of a unit root, $P$ is distributed as $\chi^2(2N)$ as $T \to \infty$ for all $i$. Choi (2001) proposes another way of combining individual $p-$values. Choi's (2001) test statistic is based on averaging the inverse $c.d.f.$ function of the standard normal distribution:

$$Z = \frac{1}{\sqrt{N}} \Phi^{-1}(pval_i) \tag{20}$$

This statistic corresponds to the standardized cross-section average of individual $p-$values. Under the assumption of cross-sectional independence of the $pval_i$, the Lindeberg-Levy CLT is sufficient to show that under the unit root hypothesis $Z$ converges to a standard normal distribution. In practice, Maddala-Wu's $P$ and Choi's $Z$ panel unit root test statistics are usually reported together under the name of either *Fisher-type*, or *combination, or pooled* tests. The pooled panel unit root tests of Maddala and Wu (1999) and Choi (2001) have important advantages:

- They do not require a balanced panel as in case of the IPS test.
- They can be carried out for any individual unit root test derived (individual tests statistics don't have to be based on the ADF).
- They allow for using different augmented terms in the individual ADF regressions.

The main disadvantage of these tests is that $p-$values have to be exact, and therefore, have to be simulated.

### 3.1.2 Cross-Section Dependence

All of the unit root tests presented in the previous section are constructed under the assumption that the individual time series of the panel are cross-sectionally independent. This condition is needed in order to satisfy the Lindberg-Levy central limit theorem, and to obtain asymptotically normally-distributed test statistics. More recently, a large literature has provided evidence of strong co-movements among economic variables. It is now recognized that the assumption of independence across members of the panel may be rather restrictive. Moreover, this cross-sectional correlation may affect the finite sample properties of panel unit root tests (O'Connell 1998).

Cross-section dependence can arise due to a variety of factors, such as omitted observed common factors, unobserved common factors, or general residual interdependence that could remain even when all the observed and unobserved common effects are taken into account. Pesaran (2004) proposes a simple test for error cross-section dependence that has correct size and sufficient power even in small samples. To check if the panel at hand is characterized by cross-section dependence, the residuals of the individual ADF regressions are used to compute Pesaran's (2004) test statistics:

$$CD = \sqrt{\frac{2}{N(N-1)}} \left( \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \sqrt{T_{i,j}} \hat{\pi}_{ij} \right) \tag{21}$$

where $\hat{\pi}_{ij}$ are the pairwise correlation coefficients among the residuals from the individual ADF regressions. Under the null hypothesis of cross-section independence, $CD$ statistic is distributed as standard normal, $N(0,1)$.

### 3.1.3 Bai and Ng (2004) Procedures: A Common Factor Model with Unobserved Common and Idiosyncratic Components of Unknown Order of Integration

Bai and Ng (2004) develop a complete set of tools to test the degree of integration of a panel with their PANIC (Panel Analysis of Non-stationarity in the Idiosyncratic and Common Components) procedure. They focus on consistent estimation of common factors and error terms of a panel data in order to test the properties of these series separately. This has two advantages; first, the factors are considered as objects of interest which can be analyzed, and second, cointegration among panel units is allowed.

The model Bai and Ng (2004) consider describes the observed data, $Y_{i,t}$, as the sum of a deterministic part, a common (stochastic) component, and the idiosyncratic error. In particular,

$$Y_{i,t} = D_{i,t} + \lambda_i' F_t + E_{i,t} \tag{22}$$

where $\lambda_i$ is a $(Kx1)$ vector of factor loadings, $F_t$ is a $(Kx1)$ vector of common factors, and $E_{i,t}$ are idiosyncratic components (error term). The deterministic component, $D_{i,t}$, contains either a constant, $\alpha_i$, or a linear trend, $\alpha_i + \beta_i t$. Bai and Ng (2004) consider a balanced panel with $N$ cross-sectional units and, $T$ time series observations.

The common factors are assumed to follow an AR(1) process:

$$F_t = F_{t-1} + f_t \tag{23}$$

where $f_t = \Phi(L)\eta_t$, and $\Phi(L) = \sum_{j=1}^{\infty} \phi_j L^j$ is a $K$-dimensional lag polynomial and rank $(\Phi(1) = k_1)$. Therefore, $F_t$ contains $k_1 \leq K$ independent stochastic trends and $K - k_1$ stationary components. The shock $\eta_t$ is assumed to be $i.i.d.$ $(0, \Sigma_\eta)$. The idiosyncratic terms are allowed to be $I(0)$ or $I(1)$, and are also modeled as $AR(1)$ processes

$$E_{i,t} = \delta_i E_{i,t-1} + e_{i,t} \tag{24}$$

where $e_{i,t}$ follows a mean zero, stationary, invertible moving average (MA) process, such that $e_{i,t} = \Gamma_i(L)\varepsilon_{i,t}$ with $\varepsilon_{i,t} \sim i.i.d.(0, \sigma^2_{\varepsilon_i})$. Bai and Ng (2004) do not assume a-priori cross-sectional independence of the idiosyncratic terms, they rather impose it later to validate pooled testing.[6]

The goal of PANIC is to determine the number of non-stationary factors $k_1$, and to test for each $i = 1, 2, \ldots, N$, whether $\delta_i = 1$. Since the factors and idiosyncratic components are both unobserved, and the objective of PANIC is to test for unit roots, the key to Bai and Ng (2004) analysis is consistent estimation of these components when it is not known a-priori whether they are $I(0)$ or $I(1)$. Bai and Ng (2004) suggest using principal components to consistently estimate the unobserved components $F_t$ and $E_{i,t}$. When $E_{i,t}$ is stationary, $F_t$ and $\lambda_i'$ can consistently be estimated regardless of the order of $F_t$. It should be noted here that if $E_{i,t}$ are $I(0)$, estimation using the data in level form is more efficient and gives a direct and consistent estimate of $F_t$ (Bai and Ng 2004; p. 1141). If $E_{i,t}$ is integrated, however, the estimator is inconsistent; because a regression of $Y_{i,t}$ on $F_t$ is spurious. Therefore, to derive consistent estimates even when some elements of $F_t$ and $E_{i,t}$ are $I(1)$, Bai and Ng

[6] The approximate factor model of Bai and Ng (2002, 2004) permits weak-form serial (and cross-sectional) dependence in the idiosyncratic component as long as $N$ (cross-section dimension) and $T$ (time-series dimension) are large. This is because dependence due to the factor structure asymptotically dominates any weak dependence in the idiosyncratic component, and well-designed criteria (e.g., Bai and Ng, 2002) can eventually determine the number of factors as both $N$ and $T$ go infinity. However, if the idiosyncratic component exhibits high serial dependence relative to the given sample size, then the factor number estimate suggested by Bai-Ng may be different (usually larger) from the truth with some probability.

(2004) use a suitable transformation of $Y_{i,t}$. In particular, if the data generating process does not contain a deterministic linear trend, the first differences of the data are used in the factor analysis; in the presence of a deterministic linear trend, demeaned first-differences are used. In other words, in the former case, $y_{i,t} = \Delta Y_{i,t} = Y_{i,t} - Y_{i,t-1}$, and in the latter case $y_{i,t} = \Delta Y_{i,t} - \Delta \bar{Y}_{i,t}$ where $\Delta \bar{Y}_{i,t} = \frac{1}{T-1} \sum_{t=2}^{T} \Delta Y_{i,t}$. Since the estimated common factors and idiosyncratic errors –denoted as $f_t$ and $e_{i,t}$, respectively– are derived applying the method of principal components to first-differenced or detrended data, Bai and Ng (2004) propose re-accumulating them to remove the effect of possible over-differencing:

$$\hat{F}_t = \sum_{s=2}^{t} \hat{f}_s \tag{25}$$

$$\hat{E}_{i,t} = \sum_{s=2}^{t} \hat{e}_{i,s} \tag{26}$$

Bai and Ng (2004) propose testing the estimates in equations 25 and 26 individually for unit roots. For the idiosyncratic components, Bai and Ng (2004) suggest computing ADF statistics based on up to $p$ lags. Denote the $t-$statistics to test the unit root hypothesis for each $\hat{E}_{i,t}$ as $ADF^{c}_{\hat{E}_i}$ or $ADF^{\tau}_{\hat{E}_i}$, depending on whether a constant, or a constant and linear trend is included in the data generating process. Bai and Ng (2004) derive the limiting distributions, which are nonstandard. For the case where a constant is present in the data generating process given in equation 22, the distribution coincides with the usual Dickey-Fuller (1979, DF) distribution where no constant is included in the estimation. The 5% critical value is $-1.95$. If the DGP in equation 22 contains a constant and a linear trend, the limiting distribution is proportional to the reciprocal of a Brownian bridge. Critical values for this distribution are not yet tabulated, and have to be simulated.

So far, the information obtained from the cross-section dimension has only been used to consistently estimate $E_{i,t}$; it has not been used to analyze stationarity properties of $E_{i,t}$. Only when the error terms are independent will pooled testing be valid. In that case, Bai and Ng (2004) propose a Fisher-type test as suggested in Maddala and Wu (1999), using the correction proposed by Choi (2001). The test statistic, denoted as $P^c_{\hat{E}}$ or $P^\tau_{\hat{E}}$ depending on the specification of deterministic terms, is given by

$$P^c_{\hat{E}} = P^\tau_{\hat{E}} = \frac{-2\sum_{i=1}^{N} log(pval_i) - 2N}{\sqrt{4N}} \tag{27}$$

where $pval_i$ is the $p$-value of the ADF test for the $i-$th cross-section. These two panel unit root test statistics have standard normal limiting distributions.

Depending on whether there is just one or several common factors, Bai and Ng (2004) suggest using either an ADF test based on up to $p$ lags, or a rank test for $\hat{F}_t$. If there is only one common factor, Bai and Ng (2004) find that conventional DF distributions can be used to test for unit roots in that single common factor. Denote the $t-$statistic for the unit root hypothesis as $ADF^c_{\hat{F}}$ when only a constant is included, and as $ADF^\tau_{\hat{F}}$ in the linear trend case. Bai and Ng (2004) derive the limiting distributions of these tests statistics, which coincide with the DF distributions for the cases where only a constant, or a constant and a linear trend are included in the ADF estimation. The asymptotic 5% critical values are $-2.86$ and $-3.41$, respectively.

If there are $K > 1$ common factors, Bai and Ng (2004) suggest an iterative procedure, comparable to the Johansen's trace test for cointegration to select $k_1$. They use demeaned or detrended factor estimates, depending on whether model 22 contains only a constant, or a constant and linear trend. The details on unit root and cointegration tests for multiple common factors can be found in Bai and Ng (2004).

## 3.2 Nonstationary or Nonlinear?

The ADF unit root tests that are applied in Bai-Ng procedures are linear in a way that the null hypothesis of a linear unit root is tested against a linear stationary model. One problem with the existing unit root tests is their low power against nonlinear-but-stationary alternatives (Caner and Hansen 2001). This has important implications for testing the present value models; if the spread series (or the estimated common factor in county-level spread data) are nonlinear, then the conventional ADF-type unit root tests may not reject the false unit root null. This problem arises because a time series with nonlinearities or structural breaks often generates a sample path that is similar to that of a unit root process in a finite sample.

A large literature has grown regarding testing the unit root null hypothesis against a stationary time series that exhibit nonlinearities or breaks. For example, Perron (1989) and Balke and Fomby (1997) consider structural break models and threshold models, respectively. In particular, Balkey and Fomby's (1997) work has realized broad applied attention to this testing problem by introducing threshold cointegration. They consider a self-exciting threshold autoregression (SETAR) in which the threshold variable is the dependent variable in lagged form. Enders and Granger (1998) propose a momentum threshold autoregression (M-TAR) model in which the threshold variable is based on a difference of the series. Caner and Hansen (2001) develop an asymptotic theory for M-TAR models and propose bootstrapping for testing threshold autoregressive models. Unit root tests for SETAR models are proposed by Bec, Ben Salem, and Carrasco (2004), and Kapetanios and Shin (2006). Finally, Seo (2008) suggests block-bootstrapping for tests of unit root hypothesis in a SETAR setting.

Testing (for linearity) in the context of threshold models is algebraically similar to testing for structural change of unknown timing. Both testing problems fall in the class of tests that involve unidentified nuisance parameters under the null, which have been studied by Davies (1987), Andrews and Ploberger (1994), and Hansen (1992, 1996) among others. This testing problem becomes more complicated if one is interested in testing a null of nonstationarity against the nonlinearity hypothesis. Although both SETAR and M-TAR models appear similar at first, each demands a distinct distribution theory depending on how nonlinearity and nonstationarity are combined in the model. For this reason, in this essay, the nonlinearity in common factors of Iowa counties' spread series is examined in more of a heuristic way rather than trying to establish the exact distributional properties of the nonlinearity and nonstationarity tests.

The threshold model used is

$$\Delta y_t = \begin{cases} \alpha^1 + \rho^1 y_{t-1} + \gamma^1 \Delta y_{t-1} + u_t & if\ y_{t-1} \geq \kappa \\ \alpha^2 + \rho^2 y_{t-1} + \gamma^2 \Delta y_{t-1} + u_t & if\ y_{t-1} < \kappa \end{cases} \tag{28}$$

where $\kappa$ is an unknown threshold parameter and $y_t$ is the estimated common factor, $\hat{F}_t$, obtained from Bai and Ng (2004) procedures. $\hat{F}_t$ represents a common factor in the panel data comprised of logarithms of cash rents-to-prices for Iowa counties. When linear ADF models applied in Bai-Ng procedures can't reject the null hypothesis of nonstationarity in common factors (regardless of the stationarity of idiosyncratic components), it implies that the log differences of cash rents and land values are not mean-reverting towards a long-run equilibrium, which is an argument that is at odds with the implications of the present value model. Therefore, it is argued with model 28 that the adjustment towards long-run might be a self exciting threshold process that is based on last period's value of $y_t$.[7] Allowing for a nonlinear adjustment process is motivated by relaxing the assumption of frictionless land markets to help explaining the anomalous behavior of farmland prices compared to the cash rents they provide. An implication of frictions in the market for a particular asset, such as land, is that they prevent agents from transacting as much of that asset as they would like. This means that the price of the asset (and therefore, spread) need not behave in the same manner as it should in the absence of frictions. In particular, it is possible for the spread of farmland to contradict the long-run stationary behavior hypothesized by a frictionless theoretical model – such as present value model– but still be consistent with the implications of the same model that is modified to allow for market frictions (Lence and Miller 1999).

Following Hansen (1996, 1997) and Caner and Hansen (2001), the unknown threshold parameter $\kappa$ in model 28 is estimated via a grid search over possible values of the threshold variable, $\Lambda = [\kappa_1, \kappa_2]$. The least-squares estimate of $\kappa$ is found by

[7]Bai-Ng procedures allow for separate tests on common factors and idiosyncratic components as the distribution of these tests are asymptotically independent of each other (Bai and Ng 2004; p. 1132).

$$\hat{\kappa} = argmin_{\kappa \in \Lambda} \hat{\sigma}^2(\kappa) \tag{29}$$

where $\hat{\sigma}^2(\kappa)$ is the least-squares estimate of residual variance for a given $\kappa$. Slope estimates are obtained after plugging $\hat{\kappa}$ in equation 28. Each regime is ensured to have a sample size of at least 15% of the total number of observations.

# 4 Data and Empirical Findings

County-level data on Iowa farmland are used for the empirical analyses. Farmland prices are based on estimates of the value of all farmland per acre, obtained from the Extension Department at Iowa State University. Data from Iowa State University are considered to be a reliable measure of average Iowa farmland prices ( Falk (1991)). Iowa State University's extension department conducts a farmland value survey since 1941; historic farmland values starting from 1950 are available to public from their web site.[8] Figures 3 and 4 illustrate recent farmland values in Iowa counties. Historic county-level cropland rental rates are obtained from the same source.[9] Although some of the cropland rental rate series in the original data set start from 1978, data for most counties start only after 1987. Some counties have very short time series data on cropland cash rents; these counties are excluded from the panel. As a result, county-level farmland price and cash rents between 1987 and 2010 for 73 Iowa counties (out of 99) are used to construct a balanced panel of the logarithms of cash rents-to-price ratios (i.e. the spread).

The econometric analyses considered in this chapter consist of two steps. First, the logarithmic rent-to-value ratios of Iowa counties are tested for unit roots assuming that the underlying process is a linear autoregressive process. Both univariate unit root tests and

[8] Only the state average and the district averages are based directly on the Iowa State survey data. The county estimates are derived using a procedure that combines the Iowa State survey results with data from the U.S. Census of Agriculture. Iowa Land Value Survey data are described in detail in the Iowa State University Extension Service's Ag Decision Maker at `http://www.extension.iastate.edu/agdm/wholefarm/html/c2-70.html`

[9] The Iowa Cash Rental Rate Survey data are described in the Iowa State University Extension Service's Ag Decision Maker at `http://www.extension.iastate.edu/agdm/wholefarm/html/c2-10.html`

tests designed for panel data are used. Issues of testing for unit roots in a panel data context are complicated when cross-sectional units show dependence. The problem of cross-sectional dependence can be addressed in numerous ways. One way is to extract the common factors of the panel data. Bai and Ng's (2004) PANIC procedures are used to estimate the number of common factors in the panel, and to test for unit roots in extracted common factors and remaining idiosyncratic components in the panel. In the second stage, nonstationarity of the common factor is further investigated by allowing for the possibility of a nonlinear, piece-wise stationary autoregressive process in the estimated common factor. To this extent, a threshold nonlinearity is assumed to be in effect in the estimated common factor of the Iowa farmland markets, where the transactions costs may create a threshold which limits adjustment in the case of shocks that are too small to imply adjustments back to steady-state levels of the spread.[10]

As a first step, univariate ADF unit root tests on spread variable are conducted for each of the 73 counties in the panel. The results are presented in Table 1. ADF regressions with both constants and linear trend terms are presented. For each county, the number of augmented terms that are necessary to remove residual autocorrelation, $p$, are computed using the Schwartz Information Criterion (SIC). The maximum lag number is assumed to be 4. One reason for using SIC in model selection is that it imposes a larger penalty for each additional augmented term; this is reasonable considering that the time-series dimension of the data is small. ADF regressions for spread in most counties do not need any autocorrelation correction, i.e. $p = 0$. The null hypothesis of unit root is rejected in 0 out of 73 cases when only a constant term is included; and, in 14 out of 73 cases when a linear time trend and a constant term are included in ADF regressions. The individual ADF tests indicate that log of cash rents-to-price ratios are nonstationary for almost all Iowa counties.

To see whether unit root tests gain power when more information is used, panel versions of ADF tests are applied as the next step of the analysis. The results of so-called first

[10]Univariate threshold autoregressive unit root tests are directly applicable to common factors since the extracted factors are univariate time series, and the distributions of test statistics of common factors and those of idiosyncratic components are independent of each other allowing for using different unit roots tests for those two components of the panel data (Bai and Ng 2004).

generation panel unit root tests are given in Table 2. The test statistics are reported with their asymptotic critical values. The numbers of augmented terms are assumed to be both homogeneous (from $p = 0$ to $p = 4$) and heterogeneous (selected via SIC) for each county. The panel unit root hypothesis is strongly rejected in case of ADF with constant term. When ADF is assumed to include a trend component, panel is found to be trend-stationary for $p = 0$; for all other choices of augmented terms, panel unit root hypothesis can't be rejected.

It is important to note that the first generation panel unit root tests suffer from severe size distortions when panel members are cross-sectionally correlated, and that the results presented in Table 2 should only be used as a guideline in the case of strong cross-section dependence. Pesaran (2004) suggests a simple test statistic, the CD test statistic, to test for the cross section correlation using the residuals from individual ADF regressions (see section 3.1.2 ). The results of Pesaran's (2004) CD tests are reported in Table 3. The results using original data (table also includes results on PANIC residuals) indicate that the null hypothesis of cross-section independence is rejected very strongly regardless of whether ADF regressions include trend or not. Furthermore, the simple average of piecewise correlation coefficients among individual spread series across all counties is considerably large (0.926), supporting the CD test results. Strong cross-section dependence among Iowa counties seems to be a characteristic of the panel data on farmland prices and cash rents.

Bai and Ng's (2004) PANIC procedure is suitable for testing for panel nonstationarity assuming that the source of cross-section dependence is the unobserved common factors in panel data. The data generating process given by equation 22 is assumed to contain only a constant term in $D_{it}$.[11] PANIC procedure requires a consistent estimate of the number of common factors. As discussed in Section 3.1.3, when the idiosyncratic components in model 22 are integrated of order zero (a condition that holds for Iowa spread data), then it is more efficient to use level data directly when estimating the factors and the loadings —$F_t$ and

[11] If there is deterministic trend in the data, this trend will be picked up by the estimated common factor. In other words, common factor can capture the potentially neglected trend components. The decision to not include trend in $D_{i,t}$, however, makes the PANIC procedure easier to implement since trend components complicate the distributional properties.

$\lambda_i$, respectively. Bai and Ng (2002) propose using model selection criteria to obtain some guidance for the factor selection. The results in Table 4 are reported for the number of maximum factors allowed changing from 1 to 8. This decision is based on the fact that in empirical applications, the performance and robustness of these selection criterion are not always consistent (see for example, Moon and Perron (2007)). Table 4 show that IC1 and IC2 criterion almost always suggest the use of as many factors as possible. On the other hand, IC3 is very robust regardless of maximum number of factor allowed; and it always suggests using one common factor. For further guidance on selecting the common factors, Table 4 also reports the eigenvalues from principal components analysis and the proportion of total variance that each eigenvalue explains. Figure 5 presents the same information as a scree plot, and it makes it easier to observe that the first eigenvalue explains over 94% of the total variation in the panel. Therefore, the rest of the PANIC analysis is based on single common factor in the data.

The results of Bai-Ng unit root tests are presented in Table 5. The top portion of the table is devoted to the results of pooled panel unit root tests on idiosyncratic components; the bottom portion gives results of the (univariate) ADF tests on the estimated common factor. All tests are presented as the augmented terms in underlying ADF regressions change from $p = 0$ to $p = 4$. $p_{BIC}$ denotes that the augmented terms are selected for each cross section unit separately based on the SIC criterion. Pooled test statistics are much larger compared to the corresponding asymptotic critical values, indicating that the idiosyncratic components of the panel are "panel stationary". It should be remarked here that the alternative hypothesis in pooled tests are of a heterogeneous type that is given in equation 17. Therefore, rejecting the null of panel unit root means that residuals for a significant portion of the panel does not contain unit root; however, the pooled tests in Table 5 are not able to show exactly how many of the Iowa counties have stationary idiosyncratic components. To confirm this, ADF tests on each idiosyncratic components are employed and the result are reported in Table 6 . The null of unit root is rejected in all counties except for Howard, Decatur and Buenavista.

An ADF test on the the estimated common factor in Table 5 indicate that the common factor has a unit root.

One appealing feature of the PANIC procedure is that it allows for inference on "cross-sectional cointegration". The presence of nonstationary factor and stationary idiosyncratic components means that the log of the ratio of cash rents to farmland prices in the panel data used are cointegrated. In other words, time series on the spread variable in Iowa counties seem to have unit roots individually; however, they move together throughout the sample period.

Overall, the standard PANIC procedure shows that the panel data on spread in Iowa counties are nonstationary since the unit root in common factor component can't be rejected. Therefore, the source of nonstationarity in $log(cash\ rents/prices)$ in Iowa counties seems to be the latent common factor. It is often useful to determine whether the estimated common factor proxies some variable of interest. A natural candidate for the first common factor in a data set is the cross-sectional averages of the variable at hand.[12] Figure 6 plots the cross-sectional averages of spread and the estimated factor in the same figure. The estimated common factor looks like a mirror image of the cross-sectional averages. Principal components analysis causes the sign to switch. To verify this observation, the common factor is regressed on the cross-section averages of the data. The resulting regression is

$$\hat{f}_t = -2.82 - 1.01\bar{y}_t + \varepsilon_t$$

with $R^2 = 0.99$. Therefore, the estimated common factor approximately is *log(land values /cash rents)+a constant*; and represents the spread variable (after taking out the county-specific components).

The plots of both levels and first differences of the estimated common factor are given in Figure 7. The plot of first differences in Figure 7b indicates that the variance of the common factor increases throughout the sample period. In other words, (approximate)

[12] Sul (2005) shows formally how cross-section averages often can be used as a proxy to a single common factor in a panel.

percentage differences between land values and cash rents seem to vary more towards the end of the sample period. As the last step of the empirical analyses, dynamic properties of the common factor are investigated in a further detail. To this extent, a two-regime threshold autoregressive model is estimated, where the adjustment parameter of the ADF regression is in regime 1 if the last period (approximate) spread exceeds a threshold level; and, it is in regime 2 if the last period spread is less than this threshold parameter.

The results of threshold ADF regression for the estimated common factor $\hat{f}_t$ are presented in Table 7. The top portion of the Table gives the estimates on the coefficients of conventional linear ADF regression. One augmented term was included based on the SIC criterion in order to correct for the autocorrelation in residuals. This augmented term is kept in the threshold model. Linear ADF model indicates that the common factor, which approximately represents average (inverse) spread, is an explosive process. According to linear ADF model, state average of the percentage difference between cash rents and farmland prices are getting further apart from each other during the sample period. The threshold model reported in the bottom portion of Table 7 indicates that although the common factor $\hat{f}_t$ still looks like an explosive process in regime 2 (where $\hat{f}_t < 0.373$), the process is mean-reverting when $\hat{f}_t$ exceeds the threshold value of 0.373. The adjustment coefficient in regime 1 is $-1.692$; it is negative and statistically significant. Going back to Figure 7a and looking for the threshold parameter 0.373 on the vertical axis, one can notice that the mean-reversion does not start until about 2006.[13]

In accordance with the previous empirical studies that have used Iowa farmland data, the empirical results in this paper using both univariate-linear and panel-linear (i.e. first generation panel unit root, and standard Bai-Ng) models suggest that the PVM does not hold for Iowa farmland markets. Although the present value model provides a strong theoretical

[13]The results presented in Table 7 are obtained with a trimming value of 15%. In other words, each regime was to have at least 15% of the total number of observations. Although 15% may not be large enough to identify all the parameters, the optimal threshold turns out to determine a small number of observations in the second regime. It should be noted here that although the common factor is a single time series – and therefore; 18% of 24 times series observations gives a short time span in the second regime – these few observations contain information from the entire panel data set which has 73 cross-section units. Furthermore, the grid search was repeated by allowing each regime to have 20% total observations instead of 15%. Although the regimes were split at a different threshold values, the estimation results were quite similar to those reported in 7. Trimming does not change the overall conclusion on the threshold regression.

relationship between price of land, expected income, expected income growth, and expected opportunity costs, it is a simplification of reality. There might be several reasons for empirical failure of the present value model.

One possible explanation that is consistent with rational investor behavior is that the discount rates in the present value model might be nonstationary. At its most fundamental level, the discount rate reflects the opportunity cost of investment that contains a risk-free component and a risk premium associated with investing in farmland. Lower discount rates indicate a lower opportunity cost and will increase the price to be paid for farmland. Individuals with higher return alternatives will have a higher opportunity cost and will be willing to pay less for investing in farmland. There is also an important relationship between the discount rate and risk-free return which is usually viewed as the return on government securities. Because farmland returns are risky, farmers usually demand a higher return on it than on government securities. Consequently, changes in the risk-free return tend to cause individuals to re-evaluate their opportunity cost and adjust their discount rates. A simple linear model of present value of farmland may be overlooking the possible evolution of discount rates throughout the sample period.

According to the economic theory on asset valuation, another reason for PVM's failure might be that the Iowa farmland market might be characterized by overreactions, or rational bubbles. A rational bubble reflects a tendency for price to deviate from its fundamental value in a nonstationary manner as a result of self-fulfilling beliefs that the price depends on some variables that may be intrinsically irrelevant with respect to the asset's fundamental value (see Diba and Grossman (1988a; 1988b) for details). However, Falk (1991) argues that the presence of such bubbles seem unlikely in Iowa farmland markets. There are two main reasons that existence of rational bubbles may not be a convincing argument for farmland markets. First, rational bubbles have explosive conditional expectations, which implies that a negative-bubble cannot exist. Second, the rational bubble can, therefore, never disappear and reappear which seems in contradiction with the successions of booms and crashes observed in farmland markets.[14]

The empirical tests on the existence of explosive rational bubbles also has limitations. Evans (1991) shows that standard unit root and cointegration tests are unable to detect periodically collapsing bubbles which are more consistent with the land markets compared to rational bubbles. This class of bubbles generates non-linear series which do not follow an explosive process enough to be detected by traditional unit root and cointegration tests. Therefore, the evidence of bubbles in the data obtained from standard integration models can equivalently be interpreted as misspecification of the basic present value models. In the case that the conventional unit root tests do indicate the presence of a bubble, an appropriate interpretation is that they suggest the presence of 'something non-stationary' in the (appropriately differenced) land prices. This could be because of a bubble; however, it could also be that the unobserved fundamentals governing cash rents and discount factors are misspecified.

Given these shortcomings of the linear present value models of land prices, in the second step of the empirical analyses, a threshold model is applied to investigate nonlinearities in the spread. These non-linear models can be used to look for non-bubble explanations for the apparent anomalies in relative land prices. One particular explanation for nonlinearities might be high transactions costs in both buying/selling farmland and the rental markets of farmland. Booms and slumps in economic activity are reflected in land prices and cash rental rates, since both reflect future economic prospects. However, it is usually observed that land prices adjust faster than the fundamentals that drive them, causing changes in cash rents to be more sluggish than those in prices (Gloy et al. 2011). Part of this discrepancy between the adjustment process of cash rents and prices may be explained by large costs involved in the contract re-negotiation process. This may be induced by the fact that cropland

[14] New models of rational bubble have been developed at the beginning of the 1990's to consider the criticism of Diba and Grossman (1988b): The intrinsic bubbles (Froot and Obstfeld 1991), and the periodically collapsing bubbles (Evans 1991). These new classes of rational bubbles share a common characteristic. They are consistent with observed asset price dynamics (including farmlands) as they diminish periodically instead of diverging continuously as in case of rational bubbles.

rental contracts are usually multi-year contracts, and that it might be expensive to break these contracts early even when the changing expectations about future earnings warrant doing so. It is, therefore, possible that the adjustment towards a stationary long-run level of spread is nonlinear and only apparent when the price-to-cash rents ratio exceeds some unknown threshold. Indeed, the results on the analysis of approximate price to income ratio (a measure of deviation of land prices from the fundamental value) shows that there is evidence for the existence of two regimes (see in Table 7). In one regime, deviations are persistent and contributes to drive land prices away from intrinsic values. Instead, the other regime is characterized by strong mean-reversion in which market valuation becomes closer to fundamental values.

# 5 Concluding Remarks

Because fluctuations in farmland prices can have serious consequences for the financial well-being of the agricultural sector, numerous studies have analyzed their behavior. However, earlier empirical studies usually fail to find support in favor of the present value model. The objective of this essay is to explore whether the absence of empirical support for the present value model can be attributed to the restrictiveness of conventional time series methods. In particular, more sophisticated methods based on panel data are used to increase the power of conventional econometric tests of present value models suggested by Campbell and Shiller (1987, 1988a,b). A second contribution is to allow for the presence of frictions in farmland markets by allowing for threshold nonlinearities in the empirical model. The argument here is that the lack of consensus about farmland pricing and the explanatory power of present value models may involve the presence of market frictions. Transactions costs and large capital investments necessary to participate in the agricultural land markets may cause nonlinearities in the adjustment towards long-run equilibrium.

The empirical analysis is based on testing for unit roots in *log(cash rents/prices)*. A county-level panel data set made up of Iowa farmland prices and cash rental rates between

1987 and 2010 is used for the empirical analyses. This data set is collected by the Extension Department at Iowa State University; and to my knowledge, it has not been previously used in testing for the present value models of farmland.

Although panel data potentially include more information compared to the univariate data, there are some pitfalls to using panel data for unit root testing. Specifically, strong cross-sectional dependence among panel members causes distortions in the size of such tests, resulting in erroneous conclusions about the dynamics of the time series of interest. Empirical tests indicate a strong cross-sectional dependence in the Iowa county-level data. Bai and Ng's (2004) PANIC method is promising in terms of handling cross-section dependence and providing some useful information about the dynamics of the panel data.

PANIC allows decomposing a panel data set into its common factors and idiosyncratic components. The approach is, then, to test for unit roots in each of these two components separately. Results of Bai-Ng procedures indicate that the panel of *log(cash rents/prices)* has a single main common factor which explains almost 95% of the total variation in the data. It is found that this common factor mimics the cross-section averages of the data, and therefore, still represents the spread. Once this common factor is removed from the data, remaining idiosyncratic components become stationary and cross-sectionally independent (or, at least weakly-dependent).

However, the conventional ADF unit root test suggested by Bai and Ng (2004) for testing nonstationarity of the common factor fails to reject the null hypothesis of unit root, which in turn indicates that the spread in Iowa farmland markets are "panel nonstationary". In fact, they seem to follow an explosive process suggesting existence of rational bubbles. In other words, deviations of relative land prices from their fundamental values seem relatively persistent. According to Bai and Ng's PANIC procedures, the source of panel nonstationarity in county-level spread data is likely the common time effect in the data.

Analysis is taken a step forward to ask whether the dynamics of the estimated common factor are consistent with a two-regime self-exciting threshold autoregressive process. Allowing for a nonlinear adjustment process in the dynamic Dickey-Fuller models relaxes the assumption of frictionless land and rental markets and may help explain the anomalous behavior of farmland prices compared to the expected cash rents that farmland provides. Results from threshold estimation suggest that the adjustment in the (approximate) log of cash rents-to-prices towards a long-run, steady-state relationship can't be observed until a threshold of 0.373 is passed, which does not occur until very recently in the sample period. However, once these regimes are distinguished, the adjustment process in Iowa farmland markets is likely to obey a piecewise linear (or a threshold) process. It should be noted that the significance of the estimated threshold model along with the unit root hypothesis within threshold framework are all based on heuristic methods. The evidence on nonlinear dynamics needs to be supported with formal tests in a future study.

The empirical evidence points to more general nonlinear patterns in spread that may cause departures from fundamentals of Iowa land markets until a threshold in spread is reached. After this threshold is passed, Iowa land markets are characterized by strong mean-reversion in which market valuation becomes closer to fundamental values as predicted by the present value model.

It should be noted that the nonlinearities that lead to modeling and estimation of regime switching fundamentals could equivalently be used to highlight the arguments in favor of intrinsic and collapsing bubbles. One can as well argue that regime-switching fundamentals are a misspecified model that captures the effects of bubbles. However, in general, having a less restrictive fundamentals model –for example by allowing for time-varying discount rates, risk aversion, structural breaks, or thresholds– allows the fundamentals part of the model to fit the data better, leaving less room for a bubble.

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## Tables and Figures

Table 1: ADF Test Results for Individual Counties (Variable: $log(\frac{CashRents}{Price})$)

| | With Constant | | | With Constant and Trend | | |
|---|---|---|---|---|---|---|
| **County** | **p** | **rho** | ***p*-value** | **p** | **rho** | ***p*-value** |
| Adair | 0 | 0.674 | 0.989 | 0 | -1.755 | 0.693 |
| Adams | 0 | -0.597 | 0.853 | 0 | -2.330 | 0.403 |
| Allamakee | 0 | 0.117 | 0.960 | 0 | -3.455 | 0.069* |
| Appanoose | 0 | -1.006 | 0.733 | 0 | -4.271 | 0.014*** |
| Audubon | 0 | -0.026 | 0.947 | 0 | -1.580 | 0.770 |
| Benton | 0 | -0.231 | 0.921 | 0 | -2.449 | 0.347 |
| Blackhawk | 0 | 0.160 | 0.964 | 0 | -2.199 | 0.468 |
| Boone | 0 | 0.179 | 0.965 | 0 | -2.093 | 0.522 |
| Buenavista | 0 | 0.048 | 0.954 | 0 | -1.317 | 0.858 |
| Butler | 0 | 0.548 | 0.985 | 0 | -1.760 | 0.690 |
| Calhoun | 0 | -0.302 | 0.910 | 0 | -1.856 | 0.644 |
| Carroll | 0 | -0.422 | 0.890 | 0 | -1.673 | 0.730 |
| Cass | 0 | -0.148 | 0.933 | 0 | -2.248 | 0.443 |
| Cedar | 1 | -0.550 | 0.863 | 0 | -3.174 | 0.114 |
| Cerrogordo | 4 | 0.006 | 0.948 | 3 | -4.880 | 0.005*** |
| Cherokee | 0 | -0.250 | 0.918 | 0 | -1.992 | 0.575 |
| Clay | 0 | 0.509 | 0.983 | 0 | -1.171 | 0.893 |
| Clayton | 0 | 0.119 | 0.960 | 0 | -2.140 | 0.498 |
| Clinton | 0 | 0.011 | 0.950 | 0 | -1.628 | 0.750 |
| Crawford | 0 | 0.300 | 0.973 | 0 | -1.227 | 0.881 |
| Dallas | 0 | -1.278 | 0.622 | 0 | -3.206 | 0.108* |
| Davis | 0 | -0.935 | 0.758 | 0 | -4.219 | 0.015*** |
| Decatur | 1 | -0.441 | 0.885 | 3 | -3.230 | 0.107* |
| Dubuque | 0 | -0.431 | 0.888 | 2 | -4.226 | 0.016*** |
| Emmet | 0 | -0.261 | 0.917 | 0 | -1.855 | 0.645 |
| Fayette | 0 | 0.583 | 0.986 | 0 | -1.827 | 0.659 |
| Floyd | 0 | 0.511 | 0.983 | 0 | -2.508 | 0.322 |
| Franklin | 0 | -0.671 | 0.835 | 3 | -3.987 | 0.027** |
| Fremont | 2 | -0.197 | 0.925 | 0 | -3.451 | 0.069* |
| Greene | 1 | 0.168 | 0.964 | 0 | -2.986 | 0.157 |
| Grundy | 0 | -0.469 | 0.881 | 0 | -2.581 | 0.291 |
| Guthrie | 0 | -0.619 | 0.848 | 0 | -2.236 | 0.449 |
| Hancock | 0 | 0.118 | 0.960 | 0 | -2.431 | 0.355 |
| Hardin | 0 | 0.027 | 0.952 | 0 | -1.766 | 0.688 |
| Harrison | 0 | -0.075 | 0.941 | 0 | -1.723 | 0.708 |
| Henry | 2 | -0.614 | 0.848 | 2 | -2.057 | 0.538 |
| Howard | 1 | -0.256 | 0.917 | 0 | -5.413 | 0.001*** |
| Humboldt | 1 | 0.157 | 0.963 | 0 | -2.300 | 0.418 |
| Ida | 0 | -1.222 | 0.647 | 0 | -2.184 | 0.476 |
| Iowa | 2 | 0.657 | 0.988 | 0 | -2.198 | 0.468 |
| Jackson | 0 | 0.590 | 0.986 | 0 | -1.924 | 0.610 |
| Jefferson | 4 | 1.848 | 0.999 | 1 | -2.862 | 0.192 |
| Johnson | 0 | -0.265 | 0.916 | 0 | -2.075 | 0.532 |
| Jones | 0 | -0.325 | 0.907 | 0 | -2.984 | 0.157 |
| Keokuk | 0 | -0.687 | 0.831 | 0 | -2.676 | 0.254 |
| Madison | 1 | 1.952 | 1.000 | 1 | -0.644 | 0.965 |

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Table 1 – Continued

| | With Constant | | | With Constant and Trend | | |
|---|---|---|---|---|---|---|
| **County** | **p** | **rho** | ***p*-value** | **p** | **rho** | ***p*-value** |
| Mahaska | 0 | -0.237 | 0.920 | 0 | -2.524 | 0.315 |
| Marion | 0 | -0.049 | 0.944 | 0 | -2.304 | 0.415 |
| Marshall | 0 | 0.302 | 0.973 | 0 | -1.955 | 0.594 |
| Mills | 0 | 0.006 | 0.950 | 0 | -1.983 | 0.579 |
| Mitchell | 0 | -0.852 | 0.785 | 0 | -2.789 | 0.215 |
| Obrien | 0 | -0.530 | 0.868 | 0 | -1.912 | 0.616 |
| Osceola | 0 | -1.263 | 0.628 | 0 | -2.449 | 0.347 |
| Page | 0 | -0.092 | 0.939 | 0 | -2.698 | 0.246 |
| Paloalto | 0 | 0.922 | 0.994 | 0 | -1.259 | 0.873 |
| Plymouth | 0 | -0.783 | 0.805 | 0 | -2.331 | 0.403 |
| Pocahontas | 1 | 0.652 | 0.988 | 0 | -1.913 | 0.616 |
| Polk | 2 | 1.211 | 0.997 | 0 | -1.677 | 0.728 |
| Pottawat | 1 | 0.007 | 0.950 | 0 | -2.891 | 0.183 |
| Sac | 0 | -0.748 | 0.815 | 0 | -2.079 | 0.530 |
| Scott | 1 | -0.807 | 0.797 | 0 | -3.234 | 0.103* |
| Shelby | 0 | -0.366 | 0.900 | 0 | -2.088 | 0.525 |
| Sioux | 0 | -0.033 | 0.946 | 0 | -1.482 | 0.806 |
| Story | 0 | 0.212 | 0.967 | 0 | -1.806 | 0.669 |
| Tama | 2 | 0.813 | 0.992 | 0 | -3.328 | 0.087* |
| Taylor | 0 | -1.017 | 0.729 | 0 | -2.885 | 0.185 |
| Warren | 0 | -0.235 | 0.921 | 0 | -2.623 | 0.274 |
| Washington | 0 | -1.435 | 0.547 | 0 | -2.967 | 0.162 |
| Wayne | 0 | -0.973 | 0.745 | 0 | -4.411 | 0.010*** |
| Webster | 0 | -0.584 | 0.856 | 0 | -2.007 | 0.567 |
| Winnebago | 0 | -0.195 | 0.926 | 0 | -1.926 | 0.609 |
| Winneshiek | 1 | 0.258 | 0.970 | 0 | -3.527 | 0.060* |
| Woodbury | 0 | -0.804 | 0.799 | 0 | -3.067 | 0.137 |
| **Unit Root Rejected in:** | | | 0 cases | | | 14 cases |

*** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level

Number of augmented terms (p) in ADF regressions are selected based on SIC.

Table 2: Results of First Generation Panel Unit Root Tests

| | **Homogeneous augmented terms** | | | | | **Individual Augmented Terms** |
|---|---|---|---|---|---|---|
| | **p=0** | **p=1** | **p=2** | **p=3** | **p=4** | **Selected via SIC** |
| | *Constant* | | | | | |
| Levin, Lin & Chu t* | 3.536 | 8.025 | 10.209 | 12.457 | 14.047 | 5.080 |
| | [0.999] | [0.999] | [0.999] | [0.999] | [0.999] | [0.999] |
| Im, Pesaran and Shin W-stat | 11.319 | 15.090 | 15.566 | 16.120 | 15.006 | 12.739 |
| | [0.999] | [0.999] | [0.999] | [0.999] | [0.999] | [0.999] |
| ADF - Fisher Chi-square | 20.730 | 9.628 | 6.831 | 6.093 | 5.544 | 16.611 |
| | [0.999] | [0.999] | [0.999] | [0.999] | [0.999] | [0.999] |
| ADF - Choi Z-stat | 11.236 | 15.131 | 16.683 | 17.877 | 18.179 | 12.746 |
| | [0.999] | [0.999] | [0.999] | [0.999] | [0.999] | [0.999] |
| | *Constant and Linear Trend* | | | | | |
| Levin, Lin & Chu t* | -4.082 | -0.784 | 2.083 | 4.482 | 11.954 | -4.255 |
| | [0.000]*** | [0.216] | [0.981] | [0.999] | [0.999] | [0.000]*** |
| Im, Pesaran and Shin W-stat | 2.950 | -0.166 | -0.199 | -0.889 | 0.917 | -3.146 |
| | [0.002]*** | [0.434] | [0.421] | [0.187] | [0.820] | [0.001]*** |
| ADF - Fisher Chi-square | 188.630 | 134.765 | 121.081 | 130.190 | 84.493 | 195.705 |
| | [0.01]*** | [0.737] | [0.935] | [0.822] | [0.999] | [0.004]*** |
| ADF - Choi Z-stat | -2.877 | -0.278 | 0.974 | 0.336 | 3.900 | -2.918 |
| | [0.001]*** | [0.390] | [0.835] | [0.631] | [0.999] | [0.002]*** |

Numbers in brackets are p-values. *** indicates significance at the 1% level. Levin Lin Chu (2002) test assumes a common unit root process for the entire panel. All other tests allow heterogeneous unit root processes. Levin Lin Chu (1992)'s t* statistics, Im, Pesaran and Shin's (2003) W-statistic and Choi's (2001) Z-statistic are asymptotically distributed as Normal (0,1). Maddala and Wu's (1999) Fisher type statistic is asymptotically distributed as Chi Square with degrees of freedom of 2N.

Table 3: Results of Cross-Section Dependence Tests of Pesaran (2007)

| | Original Data | | Idiosyncratic Components of PANIC |
|---|---|---|---|
| **ADF Regression includes:** | **Constant** | **Constant and Trend** | **No Constant or Trend** |
| Augmented terms | | | |
| p=0 | 86.05 | 91.43 | 3.49 |
| p=1 | 97.05 | 92.29 | 3.23 |
| p=2 | 95.06 | 91.04 | 3.41 |
| p=3 | 94.31 | 86.31 | 2.98 |
| p=4 | 85.22 | 85.18 | 2.7 |
| raw data | | | 2.69 |

Test statistics is asymptotically distributed as standard Normal; therefore 1% critical value for testing the null hypothesis of cross-section independence is 2.575. Original data has average pairwise correlation coefficient equal to 0.926, whereas the average of pairwise correlation coefficients of the Idiosyncratic components is −0.005.

Table 4: Selecting the Number of Common Factors in the Data

| **maximum $r$ allowed** | **1** | **2** | **3** | **4** | **5** | **6** | **7** | **8** |
|---|---|---|---|---|---|---|---|---|
| *Criteria* | | | | *Number of Selected Factors (r)* | | | | |
| IC1 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| IC2 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
| IC3 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| Eigenvalues | 68.696 | 1.267 | 0.640 | 0.555 | 0.303 | 0.252 | 0.215 | 0.204 |
| Proportion | 0.941 | 0.017 | 0.008 | 0.007 | 0.004 | 0.003 | 0.002 | 0.002 |

Table 5: Results of Bai-Ng (2004) Panel Unit Root Tests

| **Augmented terms:** | **Test statistics** | **1% critical value** | **5% critical value** | **10% critical value** |
|---|---|---|---|---|
| | ........... *Pooled Tests on Idiosyncratic Components* ........... | | | |
| $p = 0$ | 55.420 | 2.575 | 1.960 | 1.645 |
| $p = 1$ | 41.200 | 2.575 | 1.960 | 1.645 |
| $p = 2$ | 35.038 | 2.575 | 1.960 | 1.645 |
| $p = 3$ | 33.912 | 2.575 | 1.960 | 1.645 |
| $p = 4$ | 31.503 | 2.575 | 1.960 | 1.645 |
| $p_{SIC}$ | 56.642 | 2.575 | 1.960 | 1.645 |
| | ............ *ADF Test on Estimated Common Factor* ........... | | | |
| $p = 0$ | 0.426 | -3.75 | -3.00 | -2.63 |
| $p = 1$ | 0.810 | -3.75 | -3.00 | -2.63 |
| $p = 2$ | 1.303 | -3.75 | -3.00 | -2.63 |
| $p = 3$ | 1.579 | -3.75 | -3.00 | -2.63 |
| $p = 4$ | 1.364 | -3.75 | -3.00 | -2.63 |
| $p_{SIC}$ | 0.810 | -3.75 | -3.00 | -2.63 |

$p_{BIC}$ means that the augmented terms were selected for each cross section unit separately based on SIC criterion. ADF regression with estimated common factor include a constant terms and one augmented term that is selected via SIC criteria. This test statistics has standard Dickey-Fuller distribution (Case 2). The pooled test statistics is distributed as $Normal(0, 1)$.

Table 6: ADF Tests on Individual Idiosyncratic Components

| **County** | **Augmented Terms** | **rho** | ***p*-value** |
|---|---|---|---|
| Adair | 0 | -4.778 | 0.000 |
| Adams | 0 | -3.752 | 0.001 |
| Allamakee | 0 | -3.743 | 0.001 |
| Appanoose | 0 | -3.563 | 0.001 |
| Audubon | 0 | -2.648 | 0.011 |
| Benton | 4 | -4.793 | 0.000 |
| Blackhawk | 1 | -4.498 | 0.000 |
| Boone | 0 | -2.295 | 0.024 |
| Buenavista | 1 | -1.088 | 0.242 |
| Butler | 0 | -3.836 | 0.001 |
| Calhoun | 2 | -2.792 | 0.008 |
| Carroll | 0 | -2.343 | 0.022 |
| Cass | 0 | -4.643 | 0.000 |
| Cedar | 0 | -3.640 | 0.001 |
| Cerrogordo | 0 | -2.814 | 0.007 |
| Cherokee | 0 | -3.618 | 0.001 |
| Clay | 0 | -1.720 | 0.081 |
| Clayton | 2 | -4.304 | 0.000 |
| Clinton | 1 | -3.213 | 0.003 |
| Crawford | 0 | -1.841 | 0.063 |
| Dallas | 0 | -4.625 | 0.000 |
| Davis | 0 | -4.979 | 0.000 |
| Decatur | 1 | -1.285 | 0.177 |
| Dubuque | 0 | -3.320 | 0.002 |
| Emmet | 0 | -5.289 | 0.000 |
| Fayette | 0 | -3.769 | 0.001 |
| Floyd | 0 | -5.099 | 0.000 |
| Franklin | 0 | -3.468 | 0.001 |
| Fremont | 0 | -3.772 | 0.001 |
| Greene | 0 | -5.417 | 0.000 |
| Grundy | 0 | -3.295 | 0.002 |
| Guthrie | 0 | -3.893 | 0.000 |
| Hancock | 0 | -3.292 | 0.002 |
| Hardin | 0 | -2.601 | 0.012 |
| Harrison | 0 | -3.633 | 0.001 |
| Henry | 3 | -3.135 | 0.003 |
| Howard | 1 | -1.346 | 0.160 |
| Humboldt | 0 | -3.554 | 0.001 |
| Ida | 0 | -3.206 | 0.003 |
| Iowa | 0 | -3.402 | 0.002 |
| Jackson | 0 | -4.115 | 0.000 |
| Jefferson | 1 | -3.761 | 0.001 |
| Johnson | 0 | -3.841 | 0.001 |
| Jones | 0 | -1.997 | 0.046 |
| Keokuk | 0 | -3.559 | 0.001 |
| Madison | 3 | -3.689 | 0.001 |
| Mahaska | 0 | -3.688 | 0.001 |
| Marion | 0 | -3.781 | 0.001 |

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Table 6 – Continued

| **County** | **Augmented Terms** | **rho** | ***p*-value** |
|---|---|---|---|
| Marshall | 1 | -3.422 | 0.002 |
| Mills | 0 | -3.388 | 0.002 |
| Mitchell | 4 | -3.678 | 0.001 |
| Obrien | 0 | -3.442 | 0.001 |
| Osceola | 0 | -3.688 | 0.001 |
| Page | 0 | -3.818 | 0.001 |
| Paloalto | 0 | -2.093 | 0.037 |
| Plymouth | 1 | -4.322 | 0.000 |
| Pocahontas | 1 | -1.970 | 0.049 |
| Polk | 1 | -4.532 | 0.000 |
| Pottawat | 0 | -5.021 | 0.000 |
| Sac | 0 | -3.437 | 0.002 |
| Scott | 0 | -5.038 | 0.000 |
| Shelby | 0 | -5.812 | 0.000 |
| Sioux | 0 | -2.387 | 0.019 |
| Story | 0 | -3.454 | 0.001 |
| Tama | 0 | -5.213 | 0.000 |
| Taylor | 0 | -3.225 | 0.003 |
| Warren | 0 | -3.969 | 0.000 |
| Washington | 0 | -3.083 | 0.004 |
| Wayne | 0 | -3.528 | 0.001 |
| Webster | 2 | -4.454 | 0.000 |
| Winnebago | 0 | -3.045 | 0.004 |
| Winneshiek | 0 | -4.741 | 0.000 |
| Woodbury | 1 | -3.686 | 0.001 |
| **Unit Root Rejected in:** | | | 70 cases |

ADF regression has no constant or trend term.
Number of augmented terms (p) in ADF regressions are selected via SIC.

Table 7: Estimation Results of the Threshold-ADF Model

| **Parameter** | **Estimate** | **Std. Error** | **t-value** |
|---|---|---|---|
| *Linear Model (no trend):* $\hat{f}_t = \alpha + \rho \hat{f}_{t-1} + \gamma \Delta \hat{f}_{t-1} + u_t$ | | | |
| $\alpha$ | 0.034 | 0.014 | 2.44** |
| $\rho$ | 0.031 | 0.041 | 0.75 |
| $\gamma$ | 0.128 | 0.128 | 0.54 |
| *Linear Model (with trend):* $\hat{f}_t = \alpha + \rho \hat{f}_{t-1} + \gamma \Delta \hat{f}_{t-1} + \theta t + u_t$ | | | |
| $\alpha$ | -0.153 | 0.078 | -1.97* |
| $\rho$ | -0.307 | 0.143 | -2.14** |
| $\gamma$ | 0.288 | 0.221 | 1.30 |
| $\theta$ | 0.014 | 0.006 | 2.45** |
| *Threshold Model:* $\Delta \hat{f}_t = \begin{cases} \alpha^1 + \rho^1 \hat{f}_{t-1} + \gamma^1 \Delta \hat{f}_{t-1} + u_t & if\ \hat{f}_{t-1} \geq \kappa \\ \alpha^2 + \rho^2 \hat{f}_{t-1} + \gamma^2 \Delta \hat{f}_{t-1} + u_t & if\ \hat{f}_{t-1} < \kappa \end{cases}$ | | | |
| $\alpha^1$ | 0.765 | 0172 | 4.44*** |
| $\rho^1$ | -1.692 | 0.402 | -4.20*** |
| $\gamma^1$ | 0.022 | 0.252 | 0.09 |
| $\alpha^2$ | 0.035 | 0.015 | 2.30** |
| $\rho^2$ | 0.082 | 0.051 | 1.60 |
| $\gamma^2$ | 0.288 | 0.248 | 1.16 |
| *Estimated Threshold:* | 0.373 | | |
| *% of Observations in Regime 1:* | 18 | | |
| *% of Observations in Regime 2:* | 82 | | |

*** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level. Although SIC selects zero augmented terms, one lag is added to the linear model to enable comparison with the threshold model. Although coefficient $\rho$ in case of trended linear model seems to be statistically significant, it is insignificant when the augmented term is omitted.

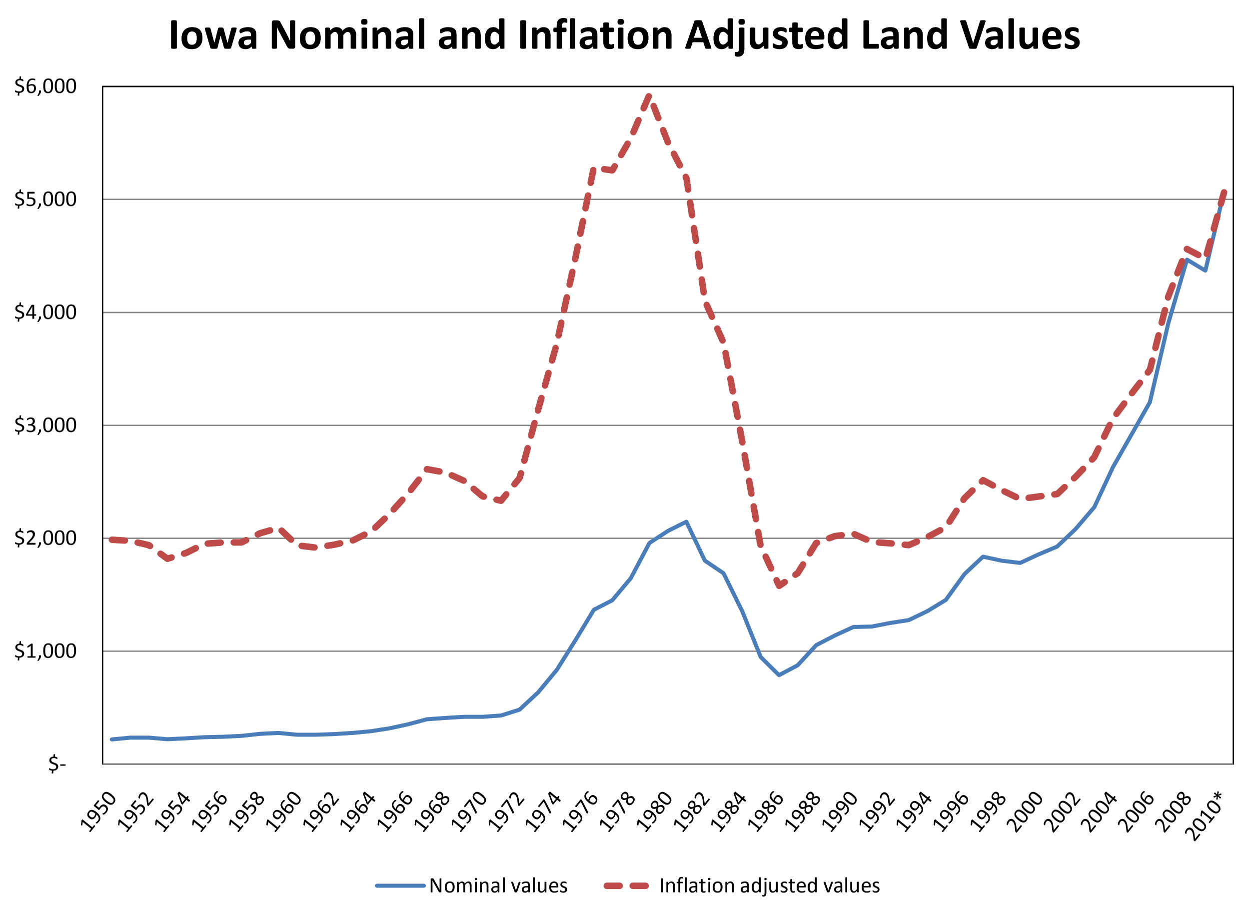



Figure 1: Inflation-Adjusted Land Values in Iowa, State Level

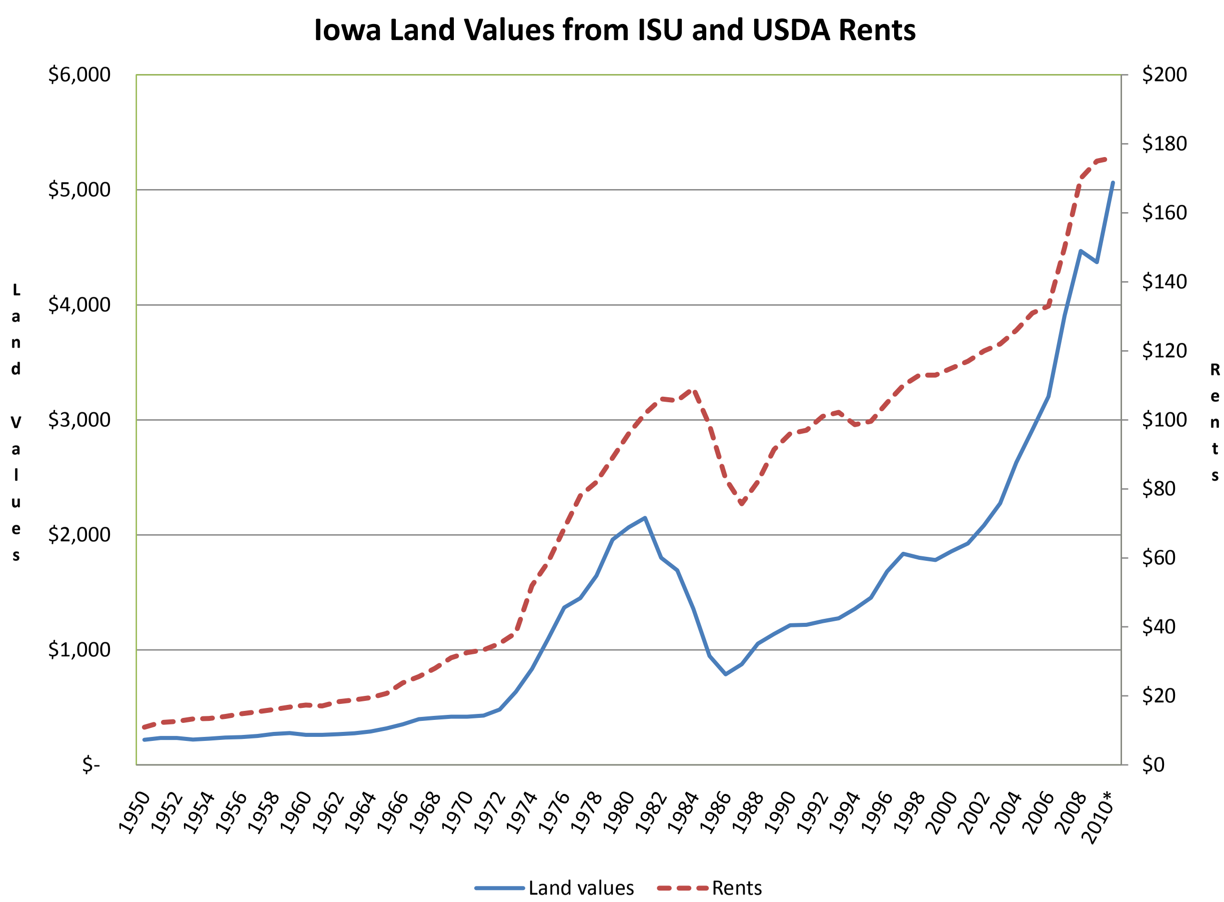



Figure 2: Iowa Land Values and Cash Rents, State Level

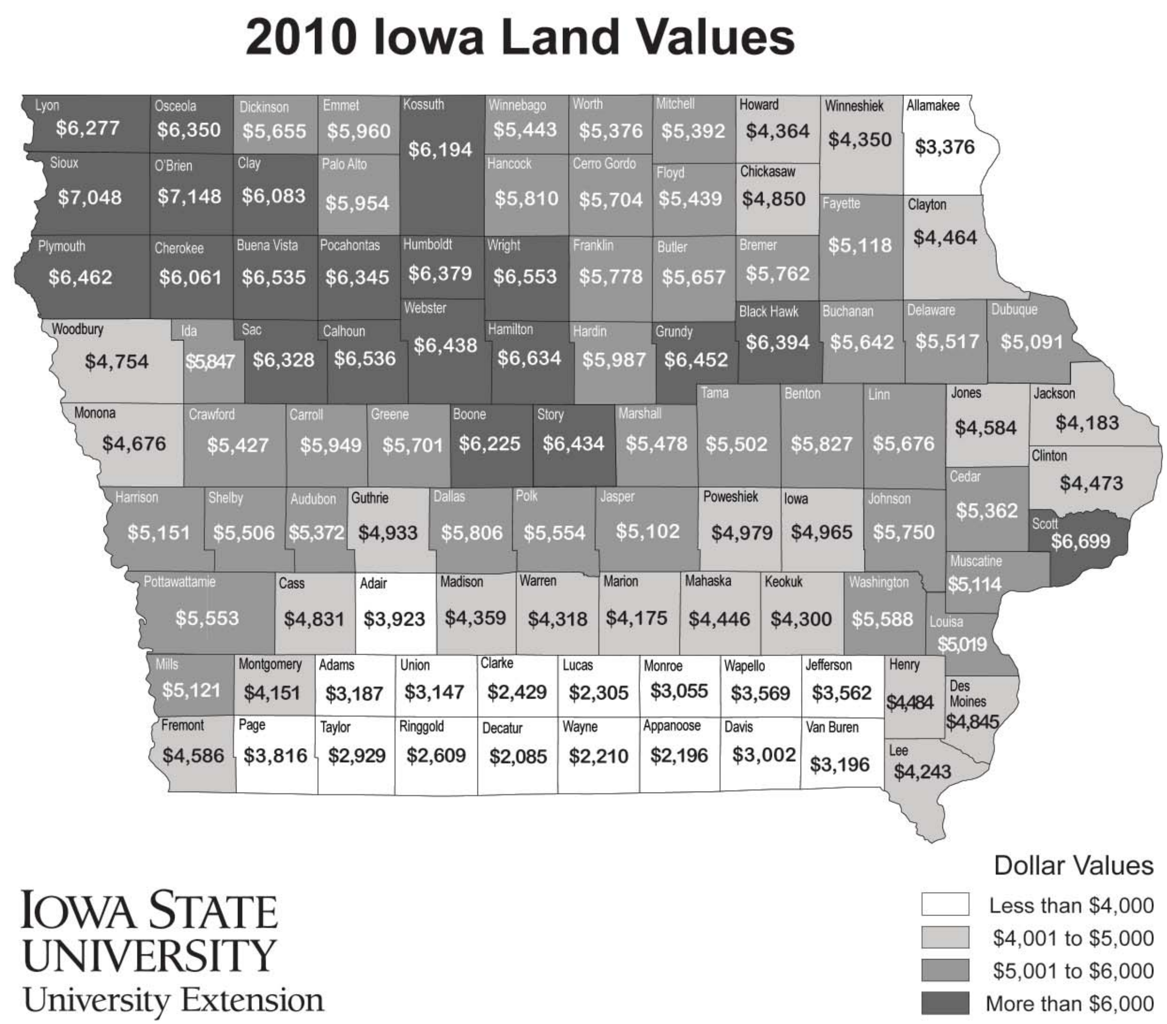



Figure 3: 2010 Iowa Land Values, County Level

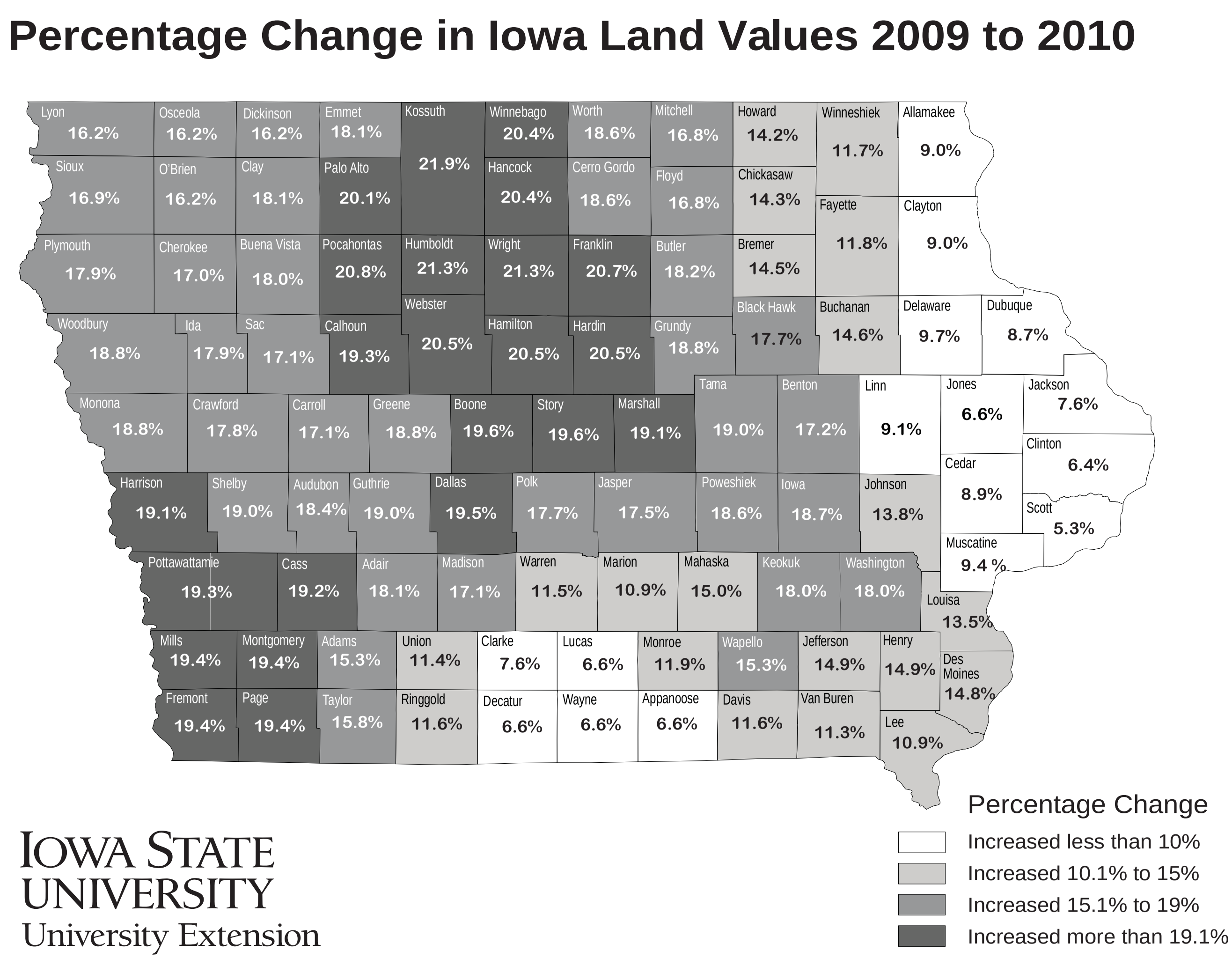



Figure 4: Percentage Change in Iowa Land Values, 2009 to 2010, County Level

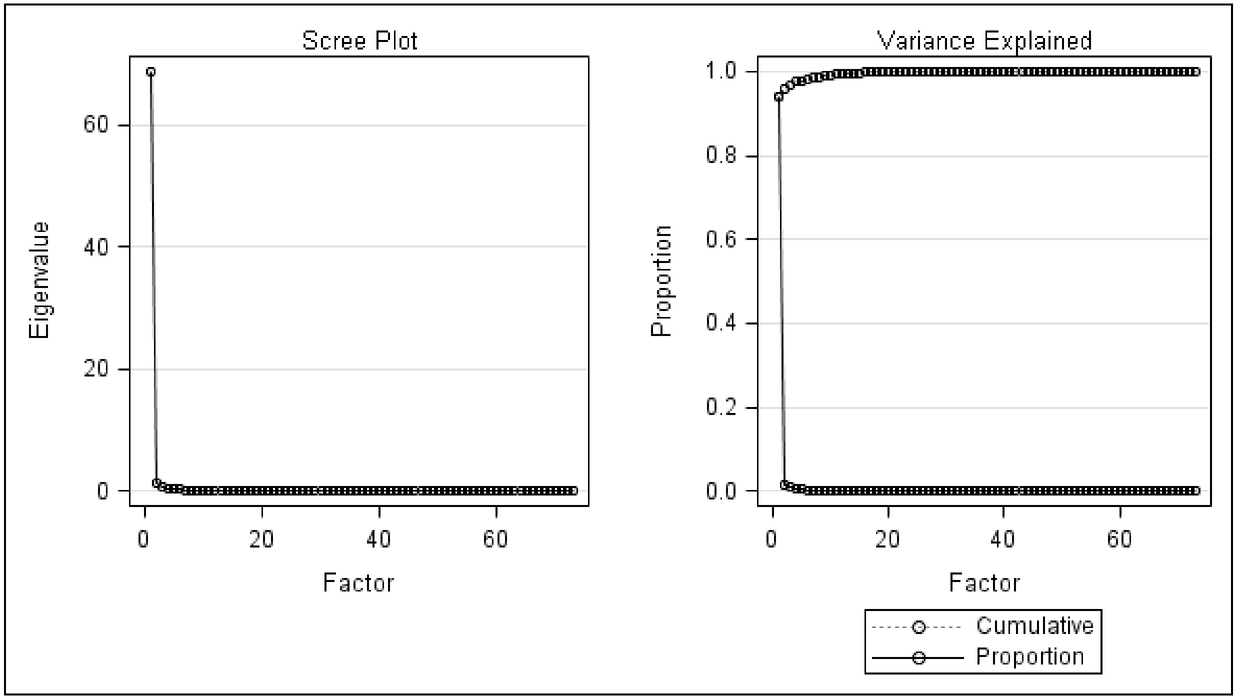



Figure 5: Scree Plot and Variance Explained by each Eigenvalue

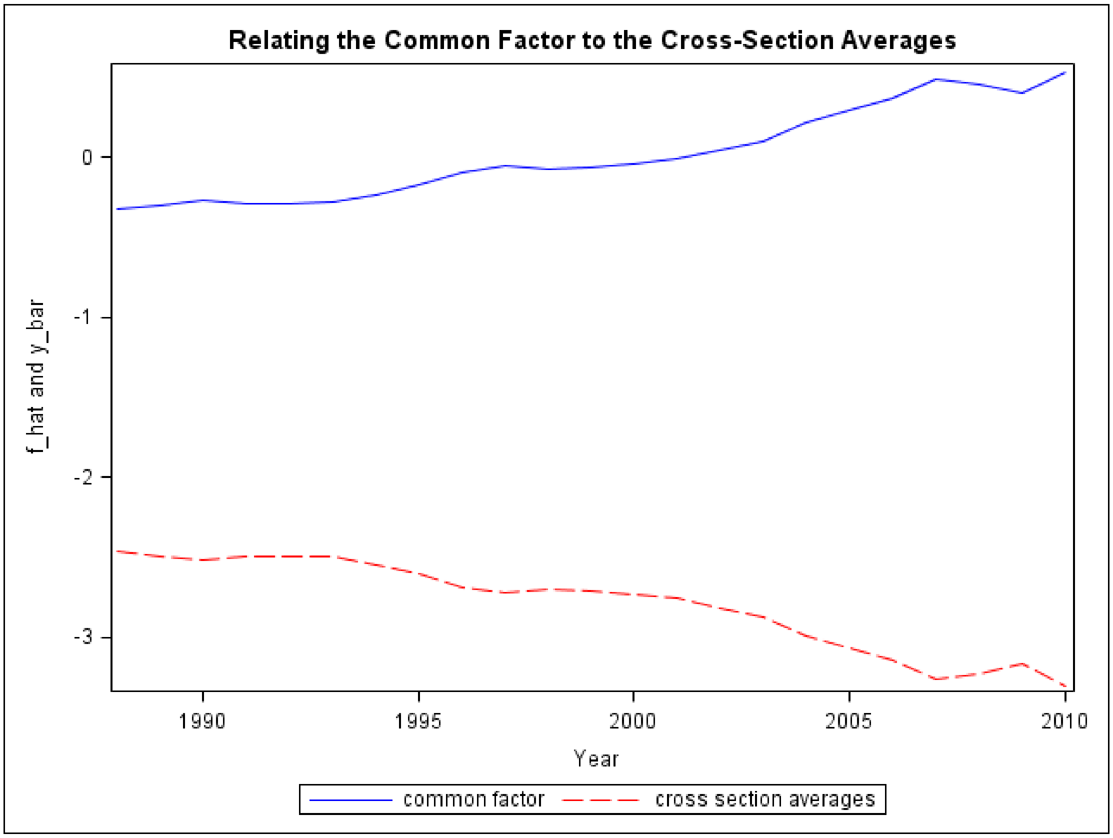
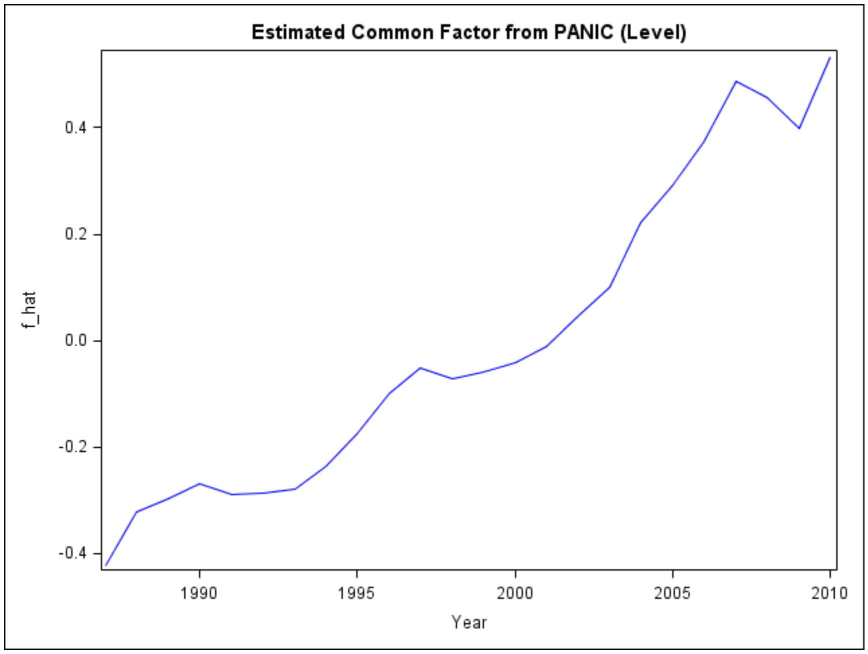
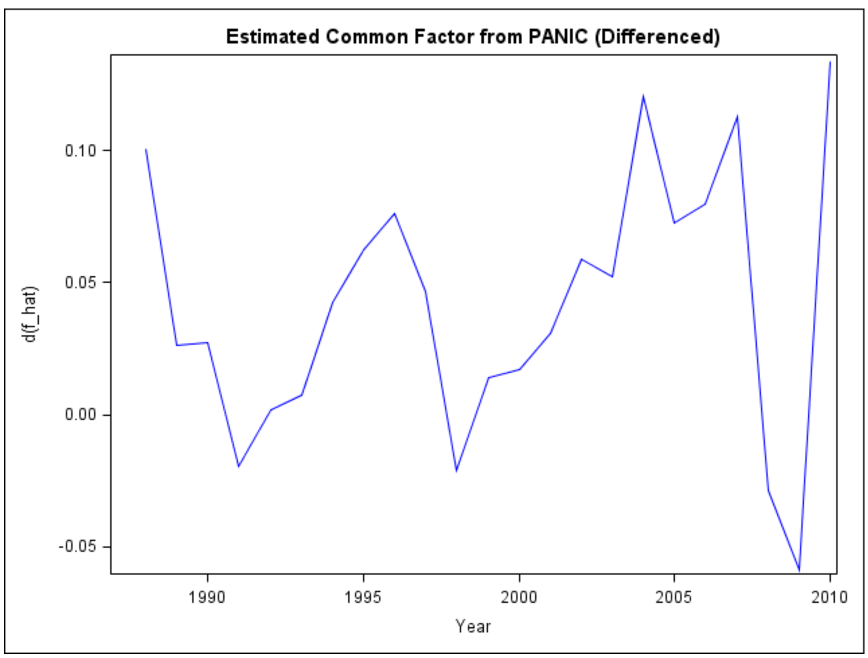



Figure 6: Estimated Common Factor and Cross-Section Averages of Spread




(a) Estimated Common Factor, Levels




(b) Estimated Common Factor, Differences

Figure 7: Estimated Common Factor from Bai and Ng's (2004) PANIC