Transaction Costs and the Present Value “Puzzle” of Farmland Prices

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Disciplines
Agricultural Economics | Econometrics | Regional Economics

Comments

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Transaction Costs and the Present Value “Puzzle” of Farmland Prices

Patrick de Fontnouvelle* and Sergio H. Lence†

The present study introduces a theoretical land pricing model that allows for proportional transaction costs, and a corresponding kernel regression test. The model is tested with farmland returns data for 20 individual states, and also with two aggregate U.S. level series. The constant discount rate (CDR) present value model (PVM) of farmland prices is strongly rejected. However, it is found that the behavior of land prices and rents is consistent with the CDR-PVM in the presence of empirically observed values of transaction costs. Findings are very robust in that they apply to both individual state-level data and the U.S. aggregate-level series.

1. Introduction

Farmland is by far the dominant asset in the U.S. agricultural sector’s balance sheet, accounting for about two-thirds of the value of all farm assets (USDA, various years). The value of U.S. farmland was estimated at $593 billion on December 31, 1994, or roughly 10% of total market capitalization for firms in the S&P 500. These figures indicate that farmland is an important asset for both the agricultural sector and the U.S. economy as a whole.

Figure 1 shows the behavior of real farmland prices in Iowa between 1900 and 1994. The time series begins with a boom in land prices between 1900 and 1916, followed by a downturn that lasted until the early 1930s. Prices then rose gradually through the 1950s and 1960s, soared in the 1970s, and plummeted once again in the 1980s. Because land has been a major source of collateral in agricultural lending, large drops in land values have typically been accompanied by substantial reductions in the availability of credit to the sector. The resulting bankruptcies have caused large-scale disruption in America’s rural economy. In states where agriculture is a dominant industry (e.g., Iowa, Kansas), these disruptions have led to major economic crises.

Because fluctuations in the price of farmland can have such serious consequences, numerous studies have attempted to explain the determinants of its value. Most of these studies are based

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† For example, between 1982 and 1988 (i.e., the most recent bust period for farmland), there were at least 16 articles in the American Journal of Agricultural Economics looking at the behavior of farmland prices.
on a frictionless present value model (PVM). The simplest version of this model, which assumes a constant discount rate (CDR), is typically rejected (Falk 1991; Clark, Fulton, and Scott 1993; Tegene and Kuchler 1993). This is a “puzzling” result because the CDR-PVM has been widely accepted and generally used for land appraisal purposes. Beyond this, however, there is surprisingly little consensus regarding the determinants of farmland prices (Pope et al. 1979; Robison and Koenig 1992; Stam 1995). A major reason for this lack of consensus may be the heterogeneity of the data sets used for empirical analysis. Different studies use different levels of aggregation, different time periods, and different land value and rent series. Hanson and Myers (1995), for example, use country-level data, whereas Tegene and Kuchler (1993) use regional data and Just and Miranowski (1993) use state-level data. Hanson and Myers (1995) use data from 1910 to 1990, Shiha and Chavas (1995) use data from 1949 to 1990, and Brown and Brown (1984) use data from 1968 to 1981. Falk (1991) examines farmland values and gross cash rents, whereas Hanson and Myers (1995) examine farm real estate values and residual returns to farm real estate.

Another possible explanation for the lack of consensus about farmland pricing, and the focus of the present study, is the presence of market frictions. Our motivation for exploring the role that market frictions might play in determining farmland prices is both theoretical and empirical. On the theoretical level, market frictions 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 thus can easily deviate from its frictionless present value. One can interpret this wedge as a band of inaction \([\lambda_L, \lambda_U]\), inside which farmers neither buy nor sell land even in the face of changing expected returns. The band is centered on the price that would prevail in the absence of transaction costs, and its width is determined by the size of these costs. On the empirical level, a review of the literature reveals that the frictionless market

---

**Figure 1.** Iowa Farmland Prices from 1900 to 1994
assumption is not a realistic representation of how farmland is actually traded. Although the costs associated with trading many financial assets are small, costs incurred in transferring ownership of farmland typically exceed 7.5% of the purchase price.

To explore the role of market frictions, we use the PVM recently used by Lence and Miller (1999), which explicitly incorporates proportional transaction costs. This model is closely related to those developed in the asset pricing literature (He and Modest 1995), and reduces to the standard PVM when transaction costs are zero. This standard PVM requires that returns to farmland satisfy a conditional moment equality restriction, which can be tested using a variety of well-developed econometric techniques (Hansen and Singleton 1982; Falk 1991). In the presence of frictions, however, the PVM implies a conditional moment inequality restriction, which corresponds to the band of inaction discussed earlier.

We use kernel regression techniques to construct a test for conditional moment inequality restrictions. Conditional moment inequalities are simply restrictions on a particular conditional expectation function, and kernel regression provides a natural way to estimate this function from the available data. We then calculate 95% uniform confidence intervals around the kernel estimate of the conditional expectation function, and reject the PVM if at least one of the confidence intervals lies entirely outside of the band of inaction $[\lambda^u, \lambda^l]$.

Kernel regressions are also attractive because they have an intuitively useful pictorial representation: a plot of expected future returns against (standardized) past returns. This plot gives a clear picture of whether statistically significant rejections of the frictionless CDR-PVM are economically significant. Under the frictionless CDR-PVM, expected returns should be constant. If the deviations of the estimated conditional expectations function from constant expected returns are small (less than 0.1%, for example), then the assumption of frictionless markets may be economically acceptable. If, on the other hand, the plots indicate consistently predictable opportunities for large trading profits, then a rejection of the frictionless PVM would seem economically significant.

To ensure that the results are as general as possible, the test is conducted over a comprehensive data set of farmland prices. This data set includes state-level data for all major agricultural states, as well as two different national series. The pictorial representation of the kernel regression also allows for a straightforward comparison of results across these different data sets: If the same economic forces are responsible for rejection of PVM in different states, then the regression functions would have roughly the same shape. We have two main empirical findings. First, the frictionless CDR-PVM is strongly rejected for most of the data sets. Second, all data sets are consistent with the standard CDR-PVM in the presence of the transaction costs typically involved in the transfer of ownership of farm real estate.

The remainder of the paper is organized as follows. Section 2 reviews the empirical literature on transaction costs for U.S. farmland. Section 3 presents a CDR-PVM that incorporates proportional transaction costs. Section 4 discusses related models of market frictions. Section 5 describes the data used in our analysis. Section 6 introduces a kernel-based test of conditional moment inequality restrictions. Section 7 reports and discusses the empirical findings, and section 8 concludes.

2. Transaction Costs for U.S. Farmland

This section reviews the empirical literature on transaction costs for U.S. farmland. Survey responses in a 1964 U.S. Department of Agriculture (USDA) study revealed that the most
popular method of farmland sale was through brokers, which accounted for 49% of voluntary sales. Direct sales and public auctions accounted for 39 and 12% of voluntary sales, respectively. The most common sales commission charged was 5% (60% of the time); other typical sales commission charges were 6 and 10% (12 and 15% of the time, respectively).

The USDA study does not report specific figures for transaction costs other than brokerage commissions, but it does provide an extensive list of such costs. Title fees (abstract, insurance, search, and stamps), surveyor’s fees, notary fees, and recording fees are commonly incurred during the sale or purchase of agricultural land. When the property itself is used as collateral, buyers must also pay appraisal fees, loan agent’s fees, document stamp fees on the mortgage, and additional recording fees.

Moyer and Daugherty (1982) calculated that transaction costs other than brokerage commissions averaged 2.5% of the purchase price of land in the United States. Their estimate was obtained from a nationwide survey conducted by the USDA on land transactions that occurred between 1975 and 1977. The figure reported by Moyer and Daugherty is consistent with that obtained by Wunderlich (1989) using data from the USDA Survey of Land Transfers. Wunderlich reported that transaction costs exclusive of sales commissions averaged 3% of the value of land transferred in the United States. According to Wunderlich, a rough approximation of the costs involved in the transfer of land ownership is 3 to 10% of the land value for brokerage fees, plus 2.5 to 3% of the land value for title insurance, legal fees, appraisals, and surveys. He also states that in some markets, total costs can be as high as 15% of the land price.

Sales that do not involve brokerage services do not incur commission costs, but still carry implicit costs because some of the broker services must be performed by the transferees at their own expense. It is also probable that such transactions may be concluded under less favorable terms: Thompson and Whiteside (1987) found that in South Carolina, farmland marketed by real estate firms averaged prices about 10% higher than farmland sold privately. Their results suggest that implicit costs in private sales can be as high or higher than explicit brokerage costs.

3. The Model

Consider the standard PVM of asset pricing (e.g., Sharpe, Alexander, and Bailey 1995, p. 580)

\[ p_{it} = \beta_{it} E(p_{it+1} + d_{it+1}), \]  

where \( p_{it} \) is the real price of asset \( i \) at time \( t \), \( \beta_{it} \) is the discount factor corresponding to asset \( i \) at time \( t \), \( E(\cdot) \) is the expectation operator conditional on information at time \( t \), and \( d_{it} \) is the real dividend paid by asset \( i \) at time \( t \). Alternately, Equation 1 may be rewritten as the condition that the expected gross rate of return equals the required gross rate of return:

\[ E(R_{it+1}) = 1/\beta_{it}, \]  

where \( R_{it+1} = (p_{it+1} + d_{it+1})/p_{it} \). The discount factor \( \beta_{it} \) equals the inverse of the required gross

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2 Examples of such services include appraisal, search, advertising, showing the property, and providing land market information.
rate of return corresponding to asset \( i \). The required rate of return specifically accounts for the risk involved in holding asset \( i \), so that \( \beta_{i, t} \) incorporates both time and risk considerations.

Equation 1 is a necessary condition for equilibrium in the market for asset \( i \). If the current price of asset \( i \) were smaller (greater) than the right-hand side of Equation 1, agents would find it attractive to buy (sell) asset \( i \) now because doing so would yield an expected return above the required return. Such a situation is inconsistent with equilibrium. Equation 1 also nests several important asset pricing models. In the capital asset pricing model (CAPM), the required return depends upon return \( i \)'s covariance with the market portfolio. In the arbitrage pricing theory (APT), the required return depends on the covariance of the asset’s return with various market-wide factors. In the consumption CAPM, the required return depends on the covariance between \( R_t \) and the agents’ intertemporal marginal rate of substitution in consumption.

Although typically neglected, an important assumption implicit in Equations 1 and 2 is that the market for asset \( i \) is frictionless. In the presence of market frictions, these restrictions may not hold even in equilibrium. If expected returns are greater than (less than) required returns, expected returns net of transaction costs may still be less than (greater than) required returns. Agents may thus have no incentive to trade even if Equation 2 is violated.

To model the effects of market frictions, we assume that all transactions are subject to a proportional transaction cost. We also assume that the same transaction cost, \( \tau_i \), applies to both purchases and sales of asset \( i \).\(^3\) In the presence of such costs, agents buying the asset at time \( t \) and selling it at time \( t+1 \) face a gross rate of return net of transaction costs equal to

\[
R_{buy, \tau+1} = \frac{(1 - \tau_i)P_{t+1} + d_{t+1}}{(1 + \tau_i)P_{t-1}},
\]

and those performing the opposite transactions face a gross rate of return net of transaction costs equal to

\[
R_{sell, \tau+1} = \frac{(1 + \tau_i)P_{t+1} + d_{t+1}}{(1 - \tau_i)P_{t-1}}.
\]

In equilibrium, it must hold that no agent wishes to either buy or sell asset \( i \), so that \( E_i(R_{buy, \tau+1}) \) cannot be greater than the required rate of return \((1/\beta_{i, t})\) and \( E_i(R_{sell, \tau+1}) \) cannot be less than the required rate of return. That is,

\[
E_i(R_{buy, \tau+1}) \leq 1/\beta_{i, t} \leq E_i(R_{sell, \tau+1}). \tag{3}
\]

Using Equation 3 together with \( R_{buy, \tau+1} \geq (1 - \tau_i)R_{l+1}/(1 + \tau_i) \) and \( R_{sell, \tau+1} \leq (1 + \tau_i)R_{l+1}/(1 - \tau_i) \) yields the following equilibrium restriction:

\[
\frac{-2\tau_i}{1 + \tau_i} \leq \beta_{i, t}E_i(R_{l+1}) - 1 \leq \frac{2\tau_i}{1 - \tau_i} = \lambda_U. \tag{4}
\]

Clearly, Equation 1 is a special case of Equation 4 corresponding to frictionless markets. This special case requires agents to react to all new information concerning future dividends,

\(^3\) The assumption that buyers and sellers pay the same transaction costs has the same testable implications as the more general assumption that they pay different transaction costs. To prove this point, suppose that buyers pay a transaction cost of \( \tau_{buy} \), and that sellers pay a different transaction cost of \( \tau_{sell} \). One can derive the moment restriction \((-\tau_{buy} - \tau_{sell})/(1 + \tau_{buy}) \leq \beta_{i, t}E_i(R_{l+1}) - 1 \leq (\tau_{buy} + \tau_{sell})/(1 - \tau_{sell}) \) by following the same arguments as in the main text. One can then show that for any values of \( \tau_{buy} \) and \( \tau_{sell} \), setting \( \tau_i = (\tau_{buy} + \tau_{sell})/(2 + \tau_{buy} - \tau_{sell}) \) reduces this restriction to Equation 4.
so that price always adjusts to the “fundamental” value given in Equation 5 below. In the presence of transaction costs, however, Equation 4 induces a band of inaction \([\lambda_i, \lambda_j]\). Inside this band, the gains from adjusting one’s portfolio in response to new information are more than offset by the losses stemming from the transaction costs involved in such adjustment.

Assuming that \(\beta_i\) is invariant with time, recursive application of Equation 1 yields the CDR version of the PVM typically used in the farmland pricing literature (Falk 1991):

\[
p_{i,t} = \sum_{s=1}^t \beta_t^{s-t} E_s(d_{i,s}).
\]

This CDR-PVM can also be derived from the constant \(\beta\) versions of the CAPM and APT, and from the consumption CAPM for the case of linear utility. The conditional moment inequality restriction corresponding to Equation 5 is similar to Equation 4, but with \(\beta_i\) substituted for \(\beta_{i,t}\). Such an expression is the basis for the empirical test used here to study farmland prices.

4. Related Work on Market Frictions

He and Modest (1995) and Luttmer (1996) have previously investigated how market frictions affect the empirical performance of consumption-based asset pricing models. Extending techniques developed by Hansen and Jagannathan (1991), these authors use asset return data to derive volatility bounds on agents’ intertemporal marginal rate of substitution in consumption.4 The advantage of such techniques over traditional conditional moment tests (Hansen and Singleton 1982) is that one need not compute the intertemporal marginal rate of substitution (which requires specifying the agents’ utility function) to calculate the volatility bounds. One can thus obtain a clear picture of the restrictions implied by the returns data without making any \textit{a priori} behavioral assumptions. The CDR-PVM (Equation 5), however, does not make explicit use of the intertemporal marginal rate of substitution, so that in this case the volatility bounds technique has no clear advantage over direct examination of the conditional moment restriction (Equation 4).5

In the land pricing literature, the frictionless assumption has recently been relaxed by Shiha and Chavas (1995) and Lence and Miller (1999).6 Shiha and Chavas extend the CAPM by allowing for barriers to external equity capital flows into farm real estate markets, but assume zero transaction costs otherwise. Lence and Miller (1999) develop a bootstrap method to test models allowing for nonzero costs of transferring farmland ownership. They apply their test to a long time series of farmland values and rents for Iowa, arguably the most traditional agricultural state in the United States. Lence and Miller find Iowa farmland prices consistent (incon-

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4 The intertemporal marginal rate of substitution is defined as \(\delta u'(c_{-t}, c_t)/u'(c_t)\), where \(\delta\) denotes an agent’s rate of time preference and \(u'(c_t)\) denotes her marginal utility of consumption in period \(t\).

5 The present study uses the CDR version of the PVM because there is no readily available consumption data for farm households. Obtaining such data remains an important endeavor for future research. With such data, a test based on volatility bounds and an extension of the methods proposed in this paper would both be feasible empirical projects to pursue. We argue in the conclusion, however, that such extensions are unlikely to alter the basic implications of the present results.

6 Jost and Miranowski (1993) and Chavas and Thomas (1999) have also examined farmland prices in the presence of transaction costs. However, the derivation and estimation of their models are subject to several difficulties, both practical and technical, that are discussed at length in Lence (2001).
sistent) with the CDR-PVM in the presence of typical transaction costs assuming a one-period (an infinite-period) holding horizon.

The present study differs from Lence and Miller in two fundamental ways. First, the empirical method developed here relies on kernel regression rather than bootstrapping. A clear advantage of the former method over the latter in the present context is that kernel regression allows us to fit potential nonlinearities implied by the band of inaction.\footnote{For example, in equilibrium expected returns cannot depend linearly on past returns through the whole space of past returns (e.g., see Figure 2a-d). This is true because equilibrium precludes expected returns from depending on past returns outside the band of inaction, even though inside the band expected returns may depend linearly on past returns. In contrast, Lence and Miller fit the best (linear) ARIMA model to the return series, and then use the corresponding residuals to perform the bootstrap. Hence, their method assumes a linear dependence of expected returns on past returns.} Second, unlike Lence and Miller, who only use data for a single U.S. state, the present analysis is based upon a much larger data set consisting of state-level series for as many as twenty U.S. states, plus two alternative country-level series and the Iowa series used by Lence and Miller. To our knowledge, no single farmland valuation study has analyzed as many series as the present one. The obvious advantage of relying on such a comprehensive data set is that results are much less likely to depend on the particular series chosen for analysis.

5. Data

As discussed earlier, previous studies have used different data sets and periods of analysis. To verify the robustness of our results, the model is tested against most available data sets used in the existing literature. In all instances, we follow Falk (1991) in setting $\beta_{i\ell}$ constant and equal to the inverse of the sample mean of $R_{\ell}$, In general, this choice will be the most favorable to accepting the CDR-PVM, for it guarantees that at least the unconditional version of Equation 2 is satisfied. The resulting CDRs are reported in the column headed $\beta_{i}$ of Table 1.

*State-Level Farmland Prices and Gross Cash Rents*

These two series (used for $p_{\ell,i}$ and $d_{\ell,i}$, respectively) are prepared by the USDA and are partly unpublished;\footnote{The kind assistance of John Jones at the USDA in providing the data set and related information is gratefully acknowledged.} details about their construction can be found in Barnard and Hexem (1988). The series are deflated using the All Items Consumer Price Index from *Economic Indicators* (Council of Economic Advisers, various years) and from U.S. Department of Commerce (1976). There are 26 states with no missing observations for the period 1921–1990. However, the model is estimated for only 20 states because data for the other six states seem unreliable.\footnote{The 20 states for which the model is estimated are, in order of perceived data reliability, Iowa, Illinois, Minnesota, Indiana, Ohio, Missouri, South Dakota, Wisconsin, North Dakota, Pennsylvania, Georgia, South Carolina, Mississippi, Arkansas, Michigan, Tennessee, Virginia, North Carolina, Kentucky, and Maryland. Except for Maryland, for which the series cover the period 1921–1991, data for all of the fitted states span the period 1921–1994. The six states with unreliable data are New Jersey, Maine, Delaware, Vermont, Massachusetts, and Connecticut.} The issue of data reliability is discussed in more detail in the Appendix. The analysis in the Appendix also shows that the quality of the data is somewhat questionable even for many of the 20 fitted states; the results for these states should thus be interpreted with caution.
Table 1. Results for Selected States and Aggregate U.S. Data

<table>
<thead>
<tr>
<th>Series</th>
<th>$p$-values</th>
<th>Discount Bandwidth</th>
<th>Period</th>
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<tr>
<td></td>
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<td>$\tau_1 = 1.5%$</td>
<td>$\tau_1 = 5%$</td>
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<tr>
<td>Iowa</td>
<td>0.01</td>
<td>0.59</td>
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</tr>
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<td>Illinois</td>
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<tr>
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<td>—</td>
<td>0.94</td>
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</tr>
<tr>
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<td>0.91</td>
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<tr>
<td>U.S. farm assets</td>
<td>0.27</td>
<td>—</td>
<td>0.96</td>
</tr>
</tbody>
</table>

"—" indicates that both of the point estimates $m_h(-1)$ and $m_h(1)$ lie inside the interval $[\lambda^1, \lambda^0]$. *These are the Iowa data from Lence and Miller (1999).

Iowa Data Used by Lence and Miller

The Iowa data used by Lence and Miller (1999) are unique, because Iowa is the only state for which annual farmland price and rent data are available as far back as 1900. These data are of interest because they span two price cycles: Iowa farmland prices exhibited one price cycle that peaked in 1916, and another that peaked in 1980 (see Figure 1). For this reason, and to facilitate comparison with the findings from Lence and Miller, their data were also used to perform the kernel regression tests. These data are analogous to the other state-level data described above, but span the period 1900–1994 (instead of 1921–1994), and cash rents are net of property taxes. Further details can be found in Lence and Miller (1999, p. 264).

U.S. Farm Real Estate Value and Income from Farm Real Estate

We examine these two series because they provide reasonable measures of farmland prices and dividends, respectively, and because they replicate very closely the data used previously by Hanson and Myers (1995). The income from farm real estate (IFRE) series is obtained as follows:

\[
\text{IFRE}_t = [(\text{GFI}_t - \text{GRV}_t) - (\text{TPE}_t - \text{I}_t - \text{NR}_t - \text{CC}_t)] \times \text{RETA}_t,
\]

where GFI is gross farm income, GRV is the gross rental value of operator and other dwellings,
TPE denotes total production expenses, I denotes interest, NR is the net rent to nonoperator landlords, CC is the capital consumption of operator and other dwellings, and RETA is the ratio of farm real estate value to total farm assets. The correction for operator and other dwellings is made because such dwellings are not included in the farm real estate asset values and the total farm assets series. The series are reported in Johnson (1990) and in Economic Indicators of the Farm Sector: National Financial Summary (USDA, various years), and span the period 1910–1994. Both farm real estate values and income from farm real estate are deflated using the All Items Consumer Price Index from Economic Indicators (Council of Economic Advisers, Various Years) and from U.S. Department of Commerce (1976).

U.S. Total Farm Assets and Net Returns to Farm Assets

These two series are reported in Melichar (1987); they span the period 1910–1986, and are already expressed in real terms using the implicit price deflator for personal consumption expenditures. These series have been used extensively in studies of farm real estate prices (Melichar 1979; Phipps 1984; Featherstone and Baker 1987; Clark, Fulton, and Scott 1993). The ratio \( R_{t+1} = (P_{t+1} + d_{t+1})/P_t \) is obtained as the ratio of net returns to farm assets to initial total farm assets, plus one.

6. Empirical Methods

We consider each returns series separately. This enables us to simplify notation by dropping the \( i \) subscript. In the absence of market frictions, \( \lambda^L \) and \( \lambda^U \) are both zero. The equilibrium restriction Equation 4 reduces to Equation 2, which requires the time \( t \) expected value of \( R_{t+1} \) to equal the required return \( 1/\beta_t \). This is a "no unused information" restriction: Nothing known in one period can help predict the next period’s excess returns. Setting \( H_{t+1} = \beta_t R_{t+1} - 1 \), one can rewrite this restriction as follows:

\[
E_t(H_{t+1}) = 0. \tag{6}
\]

To test Equation 6, Hansen and Singleton (1982) let \( Z_t \) denote an instrument whose value is known to agents at time \( t \). Because Equation 6 implies that such an instrument cannot help predict \( H_{t+1} \), it follows that \( E[H_{t+1}Z_t] = 0 \). This unconditional moment restriction is the basis of Hansen and Singleton’s empirical approach.

In the presence of frictions, the equilibrium restriction takes the form of the conditional moment inequality restriction Equation 4 instead of the equality restriction Equation 6. By the law of iterated expectations, Equation 4 implies:

\[
\lambda^L \leq m(z) \leq \lambda^U \quad \text{for all } z \in \mathbb{R}, \tag{7}
\]

where \( m(z) = E(H_{t+1} | Z_t = z) \). We set the instrument \( Z_t = [R_t - E(R_t)]/\sqrt{\text{Var}(R_t)} \) to be the standardized time \( t \) return on farmland.\(^{12}\)

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\(^{10}\) RETA is calculated using simple averages of beginning and ending period values for farm real estate and total farm assets.

\(^{11}\) For the years 1910–1939, the farm real estate value series was obtained from Melichar (1987).

\(^{12}\) In principle, \( Z_t \) could be vector-valued. We include only one lag of returns in \( Z_t \) because all of our data sets consist of less than 100 observations, and kernel estimation is subject to the well-known curse of dimensionality (Härdle 1990, p. 257).
To test Equation 7, we require a sample analog of \( m(z) \), that is, a way to estimate this function from the available data. Such an analog is provided by the Nadaraya-Watson kernel estimator, which is given by:

\[
\hat{m}_b(z) = \frac{\sum_{t=1}^{T} K[(z - Z_t)/b]H_{t+1}}{\sum_{t=1}^{T} K[(z - Z_t)/b]},
\]

(8)

where \( K(\cdot) \) is the standard normal density function, and \( b > 0 \) is a bandwidth parameter that regulates how much the kernel estimator \( \hat{m}_b(z) \) smoothes the observed data. This nonparametric estimator has particular appeal in the current context. In the absence of transaction costs, \( m(\cdot) \) has a simple linear parametrization. This is because \( \lambda^L = \lambda^U = 0 \) implies that \( m(\cdot) \) must be uniformly equal to zero. In the presence of transaction costs, however, theory provides no guidance concerning a parametrization for \( m(\cdot) \). All one can be sure of is that a linear parametrization would not allow \( m(z) \) to vary with \( z \) without leaving the band of inaction for large (or small) values of \( z \).

We use the cross-validation procedure described in Härdle (1990) to choose the bandwidth parameter \( b \). Under standard regularity assumptions (Bierens 1987; Härdle 1990; Robinson 1983) concerning the joint distribution of the returns \( R \) and instruments \( Z \), the Nadaraya-Watson estimator (Equation 8) evaluated at \( k \) different points converges in distribution to a multivariate normal random vector:

\[
\left( \sqrt{b} \frac{\sum_{j=1}^{k} \hat{m}_b(z_j) - m(z_j)}{\sqrt{\sigma^2(z_j)c_k f(z_j)}} \right) \xrightarrow{d} N(0, I)
\]

(9)

where \( f(z) \) denotes the marginal density of \( Z \), \( \sigma^2(z) \) denotes the conditional variance of \( H_{t+1} \) given \( Z \), and \( c_k = \int K^2(u) \, du \) is a kernel constant. We then use Equation 9, together with the Bonferroni method (Härdle 1990, p. 119), to calculate 95% uniform confidence intervals at the points \( z_1 = 1 \) and \( z_2 = -1 \). The CDR-PVM will be rejected whenever one (or both) of these confidence intervals fails to overlap the band of inaction given by \( [\lambda^L, \lambda^U] \).

7. Results and Discussion

Figure 2a presents pictorial results for the Iowa data used in Lence and Miller (1999), which is the longest available data series. Figures 2b and 2c present results for Illinois and Minnesota, two of the states with the highest quality price and rent data (see section 5). These figures plot estimated expected returns \( \hat{m}_b(z) \) for values of normalized returns \( z \) between -2 and 2. Two uniform 95% confidence intervals are plotted at the points \( z_1 = 1 \) and \( z_2 = -1 \). Horizontal lines are drawn at \( \lambda^L = -0.0296 \) and \( \lambda^U = 0.0305 \); these bounds correspond to the band of inaction induced by \( \tau = 1.5\% \) proportional transactions costs that must be paid both on purchase

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13 Bandwidth selection is subject to a trade-off between bias \( \text{E}[\hat{m}_b(z)] - m(z) \) and variance \( \text{Var}[\hat{m}_b(z)] \). If \( b \) is large, then \( \hat{m}_b(z) \) will be fairly smooth; variance will be small, but bias will be large. Conversely, if \( b \) is small, bias will be small but variance will be large. Härdle and Vieu (1991) show that cross-validation is asymptotically optimal under standard regularity assumptions. For an example of how bandwidth selection affects kernel regression estimation involving financial data, refer to Figure 2 in Lo, Mamaysky, and Wang (2000).
Transaction Costs and Farmland Prices 559

and sale of farmland. This implies total transaction costs of 3%—a likely lower bound given the empirical literature discussed in section 2.14 The figures also plot the individual data points in \([Z_r, H_{r+1}]\) space. Figure 2d presents similar pictorial results for the U.S. farm real estate series.

All four figures (2a–d) indicate that the frictionless CDR-PVM is rejected. The reason for this rejection is the same in each case: The upward-sloping regression curve indicates predictability in the gross rate of return series. In the absence of transaction costs, farmers could use this predictability to make profits as follows: If \(R_t\) is high, purchase additional land at time \(t\) and sell it at time \(t + 1\). Theory implies that positive transaction costs should reduce farmers’ ability to earn profits by trading land in this manner. This is exactly what we find empirically: For 3% transaction costs \((T_t = 1.5\%)\), the CDR-PVM is rejected only for Minnesota. For more realistic transaction costs of 6% \((T_t = 3\%)\), all four series are consistent with the CDR-PVM.

Empirical results for all reliable data sets are summarized in a different form in Table I. The \(p\) values reported in this table correspond to the maximum significance level at which restriction Equation 4 cannot be rejected for three different levels of transaction costs: 0, 3, and 6% \((T_t = 0\%, T_t = 1.5\%, \text{ and } T_t = 3\%, \text{ respectively})\). In Illinois, for example, the frictionless CDR-PVM cannot be rejected at the 1% significance level: One of the two 99% uniform confidence intervals at \(z = -1\) and \(z = 1\) exactly touches the dotted line corresponding to \(E[H_{r+1}|Z_r = z] = 0\), whereas the other confidence interval either exactly touches or contains the \(E[H_{r+1}|Z_r = z] = 0\) dotted line.

The \(p\) values in the \(T_t = 0\) column indicate that the frictionless CDR-PVM is strongly rejected for a majority of states and for the U.S. farm real estate series, whereas land values for Ohio, Pennsylvania, Virginia, Maryland, and U.S. farm assets behave in a manner consistent with the frictionless CDR-PVM.15 This fairly broad rejection of the CDR-PVM is in agreement with the findings of the previous land value literature (Falk 1991; Clark, Fulton, and Scott 1993; Tegene and Kuchler 1993). It should be noted that although the frictionless CDR-PVM is rejected for the U.S. farm real estate data, it cannot be rejected for the U.S. farm assets data. This suggests that returns on other assets included in the latter data set (e.g., inventories and machinery) have different statistical properties than returns to land alone. Mixing the two sets of returns (on land and on nonland assets) might be obscuring interesting features in each series.

Values in the \(T_t = 1.5\%\) column reveal that at the 5% significance level there are only three series (Minnesota, South Dakota, and Mississippi) of the 23 analyzed for which land values seem to behave at odds with restriction Equation 4. This restriction cannot be rejected for any of the 23 series at the 5% significance level if transaction costs are assumed to be in the low-to-average range \((T_t = 3\%\) column\).

Results for the two Iowa series are very similar: The frictionless CDR-PVM is rejected for both series, but both are consistent with Equation 4 at the usual levels of significance if \(T_t = 1.5\%\). This finding is reassuring, for it suggests that neither adding more observations (if

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14 Such low costs could be attained by assuming zero brokerage fees and typical nonbrokerage (e.g., legal) costs.

15 Nonrejection of the frictionless CDR-PVM for the four Northeastern states in the data set seems to be the only geographic pattern displayed by the figures reported in Table 1. The same is true of the graphs depicting expected returns. It must be noted, however, that a formal spatial analysis was not conducted because it was beyond the scope of the present work. Readers are referred to Benirschka and Binkley (1994) for a study of differential spatial effects in U.S. farmland prices during boom and bust periods.
they were available) to the other state-level data nor accounting for real estate taxes are likely to reverse the results reported in Table 1.

The empirical results can be summarized as follows. First, the frictionless CDR-PVM is broadly rejected by land value data. Second, the CDR-PVM is consistent with the behavior of land values and rents in the presence of typical transaction costs. Third, both of the preceding

Figure 2. Pictorial Results for (a) Iowa, (b) Illinois, (c) Minnesota, and (d) U.S. Farm Real Estate
findings are very robust in that they apply to individual state-level data as well as to U.S. aggregate-level data. This result is important because the basic sources used to calculate both data series are entirely different, that is, U.S. aggregate data are not averages of the state-level data used here.
8. Concluding Remarks

The importance of farmland for the financial health of the U.S. agricultural industry coupled with the observed boom-bust cycles in farmland prices has historically caused concern to both the farm sector and related sectors such as banking. Researchers have responded to such concerns by devoting many resources to exploring and understanding the behavior of land prices. The literature, however, has devoted little attention to the implications for farmland price behavior of the large costs typically involved in transfers of farmland ownership.

The present study introduces a kernel-based procedure that allows us to test the CDR-PVM in the presence of transaction costs. The model is tested with data corresponding to 20 individual states, and also with two aggregate U.S.-level series. Our findings are consistent with recent land value studies, in that the frictionless CDR-PVM of farmland prices is strongly rejected. However, it is found that the behavior of land values and rents is consistent with the CDR-PVM in the presence of typical transaction costs. The present results are important for two reasons. First, they confirm the seminal findings of Lence and Miller (1999) by means of a completely different testing strategy. Second, these results are quite robust, because they rely upon a much more comprehensive data set than previously used by any single farmland valuation study.

Our results suggest that, in the context of the CDR-PVM, there is nothing inherently “wrong” with the behavior of land prices. Although land markets may be considered inefficient because frictions prevent agents from reflecting in land prices all of the information available to them, it is unclear what policy could reduce such frictions. Whether it would even be a good idea to do so is an open question: Tobin (1974, 1978) has suggested that transaction costs might actually reduce price volatility in securities markets. We stress that our results in no way explain what actually causes the large swings observed in farmland prices. But they do suggest that this is an important area for future research, one that may have policy implications for farmland markets.

We have found that land price data are consistent even with the most naive version of the PVM once typical transaction costs are accounted for. Because transaction costs are so large in farmland markets, any reasonable modification (such as using consumption or interest rate data to specify a time-varying discount factor) of the CDR-PVM should imply partial equilibrium restrictions on returns that also are consistent with the data. It thus seems likely that such modifications will not yield empirically falsifiable restrictions on the time series behavior of land prices,16 and that further pursuit of this line of research may be of limited interest.

We believe that future research should instead investigate structural models aimed at explaining the root causes of swings in farmland prices. For example, Rosen, Murphy, and Scheinkman (1994) present a rational expectations model of how small exogenous shocks in demand and production can induce large cyclical fluctuations in the cattle market. Given the qualitative similarity of such fluctuations with swings in farmland prices, it seems possible that similar mechanisms might drive land price dynamics. However, they do not consider the “band of inaction” induced by transaction costs, which we have found to have such strong effects on land price dynamics. Whether land price behavior can be explained by structural models incorporating rational expectations, or transaction costs, or both, thus remains an important open

16 This situation is in marked contrast to that in other asset markets, where frictions are much smaller and the empirical performance of asset pricing models is much less clear (He and Modest 1995; Luttmer 1996).
research question. If one can account for observed swings in farmland prices as rational reactions to exogenous events, then it would seem of little consequence that transaction costs prevent prices from reacting immediately. In contrast, if fluctuations in farmland prices cannot be accounted for in such a manner—if they result instead from some deeper market inefficiency—then there may be a need for corrective policy action.

Appendix: Reliability of State-Level Data

There are two available data sets containing state-level farmland prices. The first is constructed by the USDA from surveys in which respondents indicate gross cash rents and values of the corresponding cash-rented farm real estate. We refer to this as the cash-rented (CR) data set. The USDA also publishes a second data set, containing state-level series of farm real estate values that reflect the value of all (not only cash-rented) farm real estate. We refer to this as the all-farm (AF) data set. The CR and AF data are obtained from entirely different surveys (Barnard and Hexem 1988).

In this paper, we use prices from the AF data set and rents from the CR data set. The motivation for doing so is that CR farm real estate values are likely to move closely with the value of AF real estate, and the construction of the AF real estate value series implies that such a series is of better quality than the series on CR farm real estate values (Barnard and Hexem 1988). For example, for Vermont there are 8 (13) instances in which either an annual drop greater than 25% in CR farm real estate value (gross cash rent) is followed immediately by an annual increase exceeding 25%, or vice versa. We suspect that sampling error in the CR series is responsible for such behavior, which is not surprising because the CR data are based on a much smaller sample than the AF data.

Appendix A1

Estimates of Regression (10) for Selected States

<table>
<thead>
<tr>
<th>Series</th>
<th>Point Estimates</th>
<th>Std. Deviations</th>
<th>R²</th>
<th>n(obs)</th>
</tr>
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<tbody>
<tr>
<td></td>
<td>( \phi_0 )</td>
<td>( \phi_1 )</td>
<td>( \phi_0 )</td>
<td>( \phi_1 )</td>
</tr>
<tr>
<td>Iowa</td>
<td>-0.001</td>
<td>0.97</td>
<td>0.004</td>
<td>0.04</td>
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<td>Illinois</td>
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<td>1.04</td>
<td>0.005</td>
<td>0.06</td>
</tr>
<tr>
<td>Minnesota</td>
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<td>0.97</td>
<td>0.005</td>
<td>0.06</td>
</tr>
<tr>
<td>Indiana</td>
<td>-0.004</td>
<td>1.05</td>
<td>0.005</td>
<td>0.07</td>
</tr>
<tr>
<td>Ohio</td>
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<td>0.93</td>
<td>0.006</td>
<td>0.09</td>
</tr>
<tr>
<td>Missouri</td>
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<td>0.94</td>
<td>0.050</td>
<td>0.09</td>
</tr>
<tr>
<td>South Dakota</td>
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<td>0.99</td>
<td>0.011</td>
<td>0.14</td>
</tr>
<tr>
<td>Wisconsin</td>
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<td>0.84</td>
<td>0.007</td>
<td>0.12</td>
</tr>
<tr>
<td>North Dakota</td>
<td>-0.006</td>
<td>0.96</td>
<td>0.011</td>
<td>0.15</td>
</tr>
<tr>
<td>Pennsylvania</td>
<td>0.001</td>
<td>0.91</td>
<td>0.009</td>
<td>0.15</td>
</tr>
<tr>
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<td>0.78</td>
<td>0.010</td>
<td>0.15</td>
</tr>
<tr>
<td>South Carolina</td>
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<td>0.17</td>
</tr>
<tr>
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<td>0.009</td>
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</tr>
<tr>
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<td>0.009</td>
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<tr>
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<tr>
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<tr>
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<tr>
<td>North Carolina</td>
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<td>0.68</td>
<td>0.012</td>
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<tr>
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<td>0.83</td>
<td>0.014</td>
<td>0.25</td>
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</tr>
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<td>-0.06</td>
<td>0.027</td>
<td>0.06</td>
</tr>
<tr>
<td>Maine</td>
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<tr>
<td>Delaware</td>
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<tr>
<td>Vermont</td>
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<td>0.038</td>
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<td>Massachusetts</td>
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<td>-0.03</td>
<td>0.054</td>
<td>0.16</td>
</tr>
<tr>
<td>Connecticut</td>
<td>0.043</td>
<td>0.02</td>
<td>0.041</td>
<td>0.09</td>
</tr>
</tbody>
</table>
Given the importance of data quality for the study’s purposes, a simple quantitative procedure is used to assess
data quality for individual states. More specifically, the quality of the data on CR farm real estate is assessed by means
of the regression
\[
\ln(y_{t+1}/y_t) = \phi_0 + \phi_1 \ln(x_{t+1}/x_t) + \epsilon_{t+1},
\]
where \(y_t\) is the real value of CR farm real estate at time \(t\), \(x_t\) is the real value of AF real estate at time \(t\), and \(\epsilon_{t+1}\) is an
error term. Natural logarithms of value changes are used in Equation A1 following the recommendations of Törnqvist,
Vartia, and Vartia (1985). Real values are obtained by deflating nominal values using the All-Items Consumer Price Index.

The previous discussion suggests that, unless there are unreasonably large sample errors in the CR series, fitting
Equation A1 should yield an estimate of \(\delta_0\) (\(\hat{\delta}_0\)) not significantly different from zero, an estimate of \(\phi_1\) (\(\hat{\phi}_1\)) not significa-
tically different from one, and an \(R^2\) close to one.

Results from regression Equation 10 for all 26 states that had no missing observations for the CR farm real estate
value series in the period 1921 through 1990 are summarized in Table A1. States are reported in decreasing order of
their respective \(R^2\). There are three interesting findings. First, \(\hat{\delta}_0\) is not significantly different from zero for any state.
Second and more important, there are five states for which \(\hat{\phi}_1\) is closer to zero than to one. Additional calculations
indicate that none of these is significantly different from zero. Third, there are only six states for which \(R^2\) exceeds 50%.
Given these results, it is clear that series with \(\hat{\phi}_1\) not significantly different from zero can be considered too unreliable
to pursue any further analysis. In addition, series with \(\hat{\phi}_1\) near one but with low \(R^2\) (e.g., \(R^2 < 0.25\)) seem of questionable
quality and should therefore be used and analyzed with care.

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