Dynamic Analysis of Land Prices with Flexible Risk Aversion Coefficients

Jin Xu and David Leatham
Graduate Assistant and Professor, Agricultural Economics, Texas A&M University

This paper has never be presented before and is prepared for the selected paper presentation at 2010 AAEA, CAES, & WAEA Joint Annual Meeting, Denver
July 25~27, 2010

Introduction

Although U.S. farmland values have been studied with numerous land price models, a farmland valuation puzzle still remains (Moss and Katchova, 2005). The results of traditional economic models of farmland prices demonstrate that farmland value is determined by discounted future returns to farmland (Alston 1986; Burt 1986; Featherstone and Baker 1987), but there are issues unexplained in those models.

First, farmland values exhibit significant short term boom-bust cycles that are not explained by the asset value formulations. The results of Schmitz (1995) and of Falk and Lee (1998) indicate that the values of agricultural assets are determined by market fundamentals in the long run, but in the short run farmland prices diverge significantly away from the discounted value, and these diverged periods are referred to as boom or bust cycles. Actually, more literature report the overreaction of farmland values in response to increases in returns (Featherstone and Baker 1987; Irwin and Coiling 1990; Falk 1991; Clark et al. 1993; Schmitz 1995). Second, while the direction of changes in farmland values is consistent with the capitalization formula, farmland appears to be systematically overpriced. Farmland returns are considered too low comparing with other sectors in the capital market when justified through the capital asset pricing models using their asset values.

Farmland values make up 75 percent of the U.S. agriculture assets, therefore the farmland valuation puzzle is an important problem that stimulates plenty of researches in the field. Scholars have long been trying to identify the possible causes for boom-bust cycles, such as quasi-rationality or bubbles' (Featherstone and Baker 1987), time- varying risk premiums (Hanson and Myers 1995), overreaction (Burt 1986; Irwin and Coiling 1990), fads (Falk and Lee 1998), and risk aversion and transaction costs (Just and Miranowski 1993; Chavas and Thomas 1999; Lence and Miller 1999; Lencc 2001). Further, researchers have also explored potential arbitrage barriers for overpriced farmland values, such as the absence of short selling and transaction costs make arbitrage quite risky (Chavas 2003; Lence 2003; Miller 2003).

The resolutions to the farmland valuation puzzle are interlaced with the issue of market fundamentals in the stock-pricing literature. Irwin and Coiling (1990) use a variance-bounds test proposed by Shiller (1981) and LeRoy and Porter (1981) to analyze whether the volatility in farmland prices was consistent with the variability in returns to farmland. They find that the variability in the return to farmland was potentially larger than that implied by the variability of farmland prices, but this methodology may have suffered from nonstationarity' in data series (Kleidon 1986) and small-sample bias (Flavin 1983). Campbell and Shiller (1987) develop the test of the present-value model to deal with nonstationary data. Falk (1991) uses this methodology and he does not find a stationary relationship between farmland values and returns to farmland. Hanson and Myers (1995) find that some variation in farmland values can be explained by a time-varying-discount rate, which illustrate the possible effects of nonfundamentals on farmland prices.

Falk and Lee (1998) apply the methodology proposed by Lee (1998) to examine farmland prices and they find that fads and overreactions relevant to short-run pricing behavior, while permanent fundamental shocks to long-run price movements.

Barry, Robison, and Neartea (1996) allow for the effects of risk and risk aversion on asset prices. Using a CAPM model, Shiha and Chavas (1995) uncovered statistical evidence that transaction costs have significant effects on land prices. Epstein and Zin (1991) use a nonadditive nonexpected utility based CAPM and find that risk aversion is important to farmland pricing. Kocherlakota (1996) discovers that incomplete markets and trading costs could also be relevant to the equity-premium puzzle. Just and Miranowski (1993) develop a structural model of farmland prices and find that inflation-rate and real returns on alternative uses of capital changes may cause changes in farmland values. Chavas and Thomas (1999) adopt the Epstein and zin (1991) framework in a dynamic land pricing model and both find risk aversion and transaction costs are important to the farmland prices. Lence (2001) cautions about the data stationary in Just and Miranowski (1993) and the deduction in Chavas and Thomas (1999). Plantinga et al. (2002) decompose agricultural land values through a spatial city model into components reflecting the discounted value of future land development and the discounted value of agricultural production, which counts for 91% of the overall US farmland values. Fontnouvelle and Lence (2002) find robust evidence that the behavior of land prices and rents is consistent with the CDR-PVM in the presence of empirically observed values of transaction costs. However, under the assumption of fixed relative risk aversion coefficient, the existing literatures have not fully addressed the farmland valuation puzzle.

The objective of this essay is to develop general dynamic land price models (DLPM) through the introduction of farm wealth levels, to enhance model robustness against risk aversion misspecifications. To be specific, our model generates reasonably accurate predictions for land prices, supposing that the risk aversion changes geographically and temporally (Gomez-Limon, Arriaza, and Riesgo, 2002).

Chavas and Thomas (1999) adopted the framework of Epstein and Zin (1991) and developed a DLPM that incorporates risk aversion, transaction costs, and dynamic preferences, which they applied to 1950-96 U.S. land values. Their model generates very good fitting of data, but the estimation of parameters is not stable over time and this diminishes the prediction power of the model. This essay extends the work of Chavas and Thomas by assuming that consumption has nonlinear functional forms and therefore including both return rate and wealth levels in the land pricing model. Intuitively, farm wealth levels are related to relative-risk-aversion-coefficient (Pratt, 1964; Arrow, 1965), and risk aversion affects land prices (Just and Miranowski, 1993). Consequently, the omission of farm wealth levels makes traditional pricing models especially vulnerable to risk aversion misspecifications.

We expect our empirical results to be consistent with the major findings of existing capitalization formula. Although most present value models are rejected by empirical data, and the persistent low return rate of farm sector is linked to farmland overpricing and admission of market failure, we believe that risk aversion misspecification is the missing key to the farmland valuation puzzle in those models. First, we test the hypothesized nonlinear homogeneous relationship between farmland return and wealth in our model with US data, and expect a significantly nonlinear relationship. Second, we compare the restricted and unrestricted models. We expect that the linear (restricted) estimation of risk aversion coefficient is significantly lower than that of the nonlinear (unrestricted) model, which helps to explain the apparently overpriced farmland through risk aversion misspecifications in traditional DLPM. Third, we expect better out of sample prediction of our model. Last, our model provides evidences of the structural relationship between farm wealth and the farm land prices, with the return impacts controlled in the model. Our general DLPM formula sheds light on the effect of both farm returns and wealth on farmland values through the general homogeneity assumption.

This essay will provide researchers a valuable framework in asset pricing because it develops a general DLPM that nests traditional models as its special cases. Our findings will benefit both farmers and developers with more accurate forecasts on farmland prices.

The essay proceeds as following: Section II contains a discussion and derivation of the model estimated in GMM. Section III details the construction of data, the estimation and testing procedures. Section IV illustrates the actual empirical results. Section V summarizes and concludes the essay.

The Model

We build our model with well accepted set ups for C-CAPM models. We consider the optimization problem facing a representative consumer, whose goal is to maximize his utility through his choices of levels of consumption and allocations of his portfolio among various assets each period (Mankiw and Shapiro, 1986).

At period t, the consumer's assets a_t = ($a_{0t,}$ $a_{1t,}$ $a_{2t,}$ …, a_{Kt}) are consisted with two parts: riskless assets, a_{0t}, and risky assets, (a_{1t}, a_{2t}, ...,a_{Kt}), and they come from two possible sources: assets maintained from last period, a_{t-1}, and new investments in the assets, m_t = (m_{0t}, $m_{1t,}$ m_{2t}, ..., m_{Kt}). The relationship is expressed as the following:

(1) $a_{kt} = a_{k,t-1} + m_{kt}$

k = 0, 1, 2,…, K.

At period t, consumers have the options to consume y_t and to make investment m_t. Under the assumption of rationality, the consumers are supposed to maximize their utilities in their consumption and investment decision. Therefore it is reasonable for us to assume that the the consumer's budget constraint is binding and denoted as following:

(2) $r_t a_{0,t-1} + \pi_t(a_{1,t-1}, \dots, a_{K,t-1})$

$$= q_t y_t + m_{0t} + \sum_{k=1}^{K} [P_{kt} + v_{kt}(m_{kt})] m_{kt}$$

Where $\pi_t(a_{1t-1}, a_{2t-1}, \dots, a_{Kt-1})$ is differentiable return function for risky assets, and $r_t$is the interest rate for riskless assets in period t. The function $v_{kt}(\dot{m}_{kt})$ in equation (2) represents the unit transaction cost of buying or selling asset m_{kt}. We discuss 3 scenarios for v_{kt} according to the sign of m_{kt}.

(3) $$v_{kt}(m_{kt}) = v_k^+ > 0 \quad \text{if } m_{kt} > 0,$$

$$= 0 \qquad \text{if } m_{kt} = 0,$$

$$= v_k^- > 0 \quad \text{if } m_{kt} < 0$$

We suppose that both the buyers and sellers have to pay a positive fee which would be transferred to third parties in order to close the deal, so both v_k^+, transaction cost for buying, and v_k^-, transaction cost for selling, are positive, though they may not be the same due to asymmetry, which could pose a problem to the continuity of v_{kt} at point 0. This transaction costs structure reflects a situation where transaction costs reduce the income of all market participants and discourages them from participation.

We then assume a recursive utility framework following Koopmans (1960)

(4) $$U_t = W(y_t, y_{t+1}, y_{t+2}, \dots)$$

$= U(y_t, M(U_{t+1}|I_t))$

where $M(U_{t+1}|I_t)$ is an aggregator of future consumption certainty equivalent given information I_t .

Following Epstein and Zin (1989,1991), we further assume the following:

(5a) $U_t \; = \; \left[(1-\beta)y_t^{\rho} \; + \beta M_t^{\rho}\right]^{\frac{1}{\rho}},$

for $0 \neq \rho < 1,$

$= \; (1- \; \beta)log(y_t \; + \; \beta \log(M_t),$

for $\rho = 0$

(5b) $M_t = M(U_{t+1}|I_t) = (E_t U_{t+1}^{\alpha})^{\frac{1}{\alpha}}$

if $0 \neq \alpha < 1,$

$=\exp[E_t \log(U_{t+1})]$ if $\alpha=0$

Where $\beta = 1/(1 + \delta)$, and δ is the rate of time preference. $\rho = 1 - 1/\sigma$, and σ is the intertemporal elasticity of substitution. α is the relative risk aversion coefficient of the consumer (Epstein and Zin 1989, 1991). When $\alpha = 1$, the consumer is risk neutral and the higher the value of α the more risk averse is the consumer, and vice versa.

One interesting special case of equation (5) is that when $\alpha = \rho \neq 0$, equation (5) reduces to the familiar expected time-additive utility specification

$$U_t = [(1-\beta)E_t \sum_{j\geq 0} \beta^j y_{t+j}^{\alpha}]^{1/\alpha}$$

We would test the hypothesis $\alpha = \rho \neq 0$ in our estimation results section to see if the US farmland data support time-additivity in utility function.

Assuming $U(y_t, M_t, (U_{t+1}))$ is differentiable and bounded for all feasible (y_t, a_t, m_t), the optimization problem of consumption and investment decision could be written as the following:

(6) $V_t(a_{t-1})$

$$= \max\{U\big(y_t, M_t(U_{t+1})\big)\text{: equations (1) and (2)}\}$$

$$= \max_{a_t} U\left[\left(r_t a_{0,t-1} + \pi_t - \big(a_{0t} - a_{0,t-1}\big) - \sum_{k=1}^{K} (\rho_{kt} + v_{kt})\big(a_{kt} - a_{k,t-1}\big)\right)\right.$$

$$\left. \div\, q_t, M_t\big(V_{t+1}(a_t)\big)\right]$$

where $V_t(a_{t-1})$ is the indirect objective function. Under differentiability assumptions, the first-order necessary conditions for a_t are

(7a) $a_{0t}: (\partial U/\partial y_t)/q_t = (\partial U/\partial M_t)(\partial M_t/\partial a_{0t})$

(7b) $$a_{kt}: \frac{\left(\frac{\partial U}{\partial y_t}\right)(P_{kt} + v_{kt})}{q_t} = \left(\frac{\partial U}{\partial M_t}\right)\left(\frac{\partial M_t}{\partial a_{kt}}\right), \quad \text{if } m_{kt} \neq 0$$

Noticing that we leave the case that $m_{kt} = 0$ out of our deduction due to 2 reasons. First, the functional form in equations (8) at $m_{kt} = 0$ is disputable according to Lence (2001). Second, in the data set for estimation, we do not have any data point with $m_{kt} = 0$, which could bear a nearly 0 possibility in the reality.

Apply the envelope theorem to equation (6) at points of differentiability, we have

(8a) $$\frac{\partial V_t}{\partial a_{0,t-1}} = \frac{\left(\frac{\partial U}{\partial y_t}\right)(1 + r_t)}{q_t}$$

(8b) $$\frac{\partial V_t}{\partial a_{k,t-1}} = \frac{\left(\frac{\partial U}{\partial y_t}\right)\left[\left(\frac{\partial \pi_t}{\partial a_{k,t-1}}\right) + (P_{kt}+v_{kt})\right]}{q_t} \qquad \text{if } m_{kt} \neq 0$$

According to equation (5b), we use implicit function form theorem to get

$$\partial M_t/\partial at = M_t^{1-\alpha} E_t[U_{t+1}^{\alpha-1}(\partial U_{t+1}/\partial at)].$$

Substituting equation (8a) and (8b) into equation (7a) and (7b),

(9a) $$(\frac{\partial U}{\partial y_t})/q_t = (\partial U/\partial M_t)(M_t^{1-\propto} E_t[U_{t+1}^{\propto-1}(\partial U/\partial y_{t+1})\ (1 + r_{t+1})/q_{t+1})$$

(9b) $$\frac{\left(\frac{\partial U}{\partial y_t}\right)(P_{kt} + v_{kt})}{q_t} = (\partial U/\partial M_t)\ \{M_t^{1-\propto} E_t[U_{t+1}^{\propto-1}(\partial U/\partial y_{t+1}]) \times [(\partial \pi_{t+1}/\partial a_{kt})$$

$$+(P_{k,t+1} + v_{k,t+1})]/q_{t+1}]\} \quad \text{if } m_{kt} \neq 0$$

If we substitute (9a) into (9b), and assume $\alpha = \rho = 1$, we get the standard time-additive model under risk neutrality, which we would also test in our estimation section.

(10) $$(P_{kt} + v_{kt}) = E_t\{[(\partial\pi_{t+1}/\partial a_{kt}) + P_{k,t+1} + v_{k,t+1}]/q_{t+1}\} \div E_t[1 + r_{r+1})/q_{t+1}]$$

Specification:

Equation (9a) and (9b) are the Euler equations at optimal price dynamics, but we could not use them directly to estimate future farmland prices because part of the structures is not observed. In this section, we show how to further specify the structures of equation (9a) and (9b) through testable assumptions and deduct an empirical system from them.

Assume the consumer's aggregated wealth level at period t and t-1, A_t and A_{t-1}, as following

(11a) $A_t = a_{0t} + \sum_{k=1}^{K}(P_{kt} + v_{kt})a_{kt}.$

(11b) $A_{t-1} = a_{0t-1} + \sum_{k=1}^{K}(P_{kt-1} + v_{kt-1})a_{kt-1}$

From equation (2) we can get

(12) $q_t y_t = r_t a_{0,t-1} + \pi_t(a_{1,t-1}, \dots, a_{k,t-1}) - [m_{0t} + \sum_{k=1}^{K}(P_{kt} + v_{kt})m_{kt}]$

We can rewrite equation (12) as the following

(13) $q_t y_t = \left[(r_t + 1) - \frac{a_{0,t}}{a_{0,t-1}}\right] a_{0,t-1} + \sum_{k=1}^{K}\left[\left(\frac{\partial \pi_t}{\partial a_{k,t-1}}\right) + (P_{kt} + v_{kt})\left(1 - \frac{a_{k,t}}{a_{k,t-1}}\right)\right] a_{k,t-1}$

ASSUMPTION A1. *The return function* $\pi_{t(a_{1t}, a_{2t}, \dots, a_{Kt})}$*is linear homogenous in* $(a_{1t}, a_{2t}, \dots, a_{kt})$.

ASSUMPTION A2. *The consumption function* $y_{t(A_{t-1})}$*is homogenous of degree* λ *in* A_{t-1}

or $y_t(A_{t-1})$ H. D. O. λ.

We can then write the consumption function as

(14) $y_t = k_t \cdot {A_{t-1}}^{\lambda}$

Use Taylor expansion we can rewrite (14) as

(15) $y_t = k_t \left[A_{t-1} + \frac{(\lambda-1)^1}{1!} \cdot logA_{t-1} \cdot A_{t-1} + \cdots + \frac{(\lambda-1)^n}{n!} \cdot log^n A_{t-1} A_{t-1} + \cdots\right]$

(i) when $0 \leq \lambda \leq 2, (\lambda - 1)^n \to 0 \; as \; n \to \infty$.

(ii) $A_{t-1}$is bounded, so $logA_{t-1}$is also bounded. Therefore $\frac{log^n A_{t-1}}{n!} \to 0 \; as \; n \to \infty$.

Due to (i) and (ii), we can find an integer *N*, such that

$$y_t = k_t \left[A_{t-1} + \frac{(\lambda - 1)}{1!} \cdot logA_{t-1} \cdot A_{t-1} \ldots + \frac{(\lambda - 1)^N}{N!} \cdot log^N A_{t-1} \cdot A_{t-1}\right] + \varepsilon$$

Where $\varepsilon < 0.00001$

Thus, we can write the following

(16) $y_t \doteq k_t \cdot A_{t-1} \left[1 + \frac{(\lambda-1)}{1!} \cdot logA_{t-1} \cdot A_{t-1} \ldots + \frac{(\lambda-1)^N}{N!} \cdot log^N A_{t-1} \cdot A_{t-1}\right]$

Define $R_t \equiv \frac{\partial y_t}{\partial A_{t-1}}$, under the assumption A2, Equation (14) could be rewritten as:

$$y_t = \frac{1}{\lambda} \cdot R_t \cdot A_{t-1}$$

Together with (17), we can find

(17) $R_t \doteq \lambda k_t \left[1 + \frac{\lambda-1}{1!} \cdot logA_{t-1} \cdot A_{t-1} + \cdots \frac{(\lambda-1)^N}{N!} \cdot log^N A_{t-1} \cdot A_{t-1}\right]$

Together with (13), we can find

(18) $\left[\frac{R_t q_t}{\lambda} - (r_t + 1) + \frac{a_{0t}}{a_{0,t-1}}\right] = \sum_{k=1}^{K} \frac{a_{kt-1}}{a_{0t-1}} \left[\frac{\partial \pi_t}{\partial a_{kt-1}} + (P_{kt} + v_{kt}) \left(1 - \frac{a_{kt}}{a_{k,t-1}}\right) - \frac{R_t q_t}{\lambda} (P_{kt} + v_{kt})\right]$

Equation (18) is very important, and we use it to derive the key value for our homogeneity test.

(19) $R_t = \frac{\lambda}{q_t} \cdot \frac{(r_t+1) - \frac{a_{0t}}{a_{0t-1}} + \sum \frac{a_{kt-1}}{a_{0t-1}} \left[\frac{\partial \pi_t}{\partial a_{kt-1}} + (P_{kt}+v_{kt}) \left(1 - \frac{a_{kt}}{a_{kt-1}}\right)\right]}{1 + \sum \frac{a_{kt-1}}{a_{0k-1}} (P_{kt}+v_{kt})}$

From equation (5), we can find

$$U_t(y_t, \tau M_t) = [(1-\beta)(\tau y_t)^\rho + \beta(\tau M_t)^\rho]^{\frac{1}{\rho}}$$

$$= \tau\left[(1-\beta)y_t^\rho + \beta M_t^\rho\right]^{\frac{1}{\rho}}$$

$$= \tau U_t(y_t, M_t)$$

for $0 \neq \rho < 1$

Under Assumption A2, we have $y_t = k_t \cdot A_{t-1}^{\lambda}$

$$U_t[y_t(\tau A_{t-1}), M_t(\tau A_t)] = U_t\left[\tau^\lambda y_t(A_{t-1}), \left(E_t U_{t+1}^{\alpha}(\tau A_t)\right)^{1/\alpha}\right]$$

Notice the second term is self-adjusting to the relationship of $U_t(A_{t-1})$, if we assume linear expectation operator.

We can have $U_t[\tau A_{t-1}, \tau A_t] = \tau^{\lambda} U_t[A_{t-1}, A_t]$

(20) $$V_t(\tau A_{t-1}) = max U_t(\tau A_{t-1}, \tau A_t)$$

$$= \tau^{\lambda} max U_t(A_{t-1}, A_t)$$

$$= \tau^{\lambda} V_t(A_{t-1})$$

From equation (5), we can apply the envelope theorem and get the following:

(21) $$\frac{\partial V_t}{\partial A_{t-1}} = \frac{\partial U_t}{\partial A_{t-1}} = \frac{\partial U_t}{\partial y_t} \cdot \frac{\partial y_t}{\partial A_{t-1}} = U_t^{1-\rho}(1-\beta) y_t^{\rho-1} \cdot R_t$$

Together with (20), we can have

(22) $$V_t = \frac{1}{\lambda} \cdot \frac{\partial V_t}{\partial A_{t-1}} \cdot A_{t-1} = \frac{1}{E} U_t^{1-\rho}(1-\beta) y_t^{\rho-1} \cdot R_t \cdot A_{t-1}$$

Rearrange equation (22) under the assumption that $U_t = V_t$ at optimum, we have

(23a) $$U_t = \left[\frac{1}{\lambda}(1-\beta) y_t^{\rho-1} \cdot A_{t-1} R_t\right]^{\frac{1}{\rho}} \qquad \text{for } \rho \neq 0$$

(23b) $$U_{t+1} = [\frac{1}{\lambda}(1-\beta) y_{t+1}{}^{\rho-1} A_t R_{t+1}]^{1/\rho}$$

(24) $$U_{t+1}{}^{\alpha-1}(\partial U / \partial y_{t+1}) = U_{t+1}{}^{\alpha-\rho}(1-\beta) y_{t+1}{}^{\rho-1} = [\frac{1}{\lambda}(1-\beta) y_{t+1}{}^{\rho-1} A_t R_{t+1}]^{(\alpha-\rho)/\rho}(1-\beta) y_{t+1}{}^{\rho-1}$$

From equation (5a) we can get the first derivatives:

$$\partial U_t / \partial M_t = U_t^{1-\rho} \beta M_t^{\rho-1}$$
$$\partial U_t / \partial y_t = U_t^{1-\rho} (1-\beta) y_t^{\rho-1}$$

(25) $$(\partial U_t / \partial M_t)/(\partial U_t / \partial y_t) = \beta M_t^{\rho-1} /[(1-\beta) y_t^{\rho-1}]$$

Rewrite equation (5a), we can get the following

$$M_t^{\rho} = [U_t^{\rho} - (1-\beta) y_t^{\rho}]/\beta$$

Substituting from equation (23a)

(26) $$M_t = \{[\frac{1}{\lambda}(1-\beta) y_t^{\rho-1} A_{t-1} R_t - (1-\beta) y_t^{\rho}]/\beta\}^{1/\rho}$$

Therefore the following part could be substituted using equation (24), (25), and (26)

(27) $$[(\partial U_t / \partial M_t)/(\partial U_t / \partial y_t)][M_t^{1-\alpha} U_{t+1}^{\alpha-1} (\partial U / \partial y_{t+1}) q_t / q_{t+1}]$$

$$= \{\beta M_t^{\rho-\alpha} /[(1-\beta) y_t^{\rho-1}]\}[\frac{1}{\lambda}(1-\beta) y_{t+1}^{\rho-1} A_t R_{t+1}]^{(\alpha-\rho)/\rho} (1-\beta) y_{t+1}^{\rho-1} q_t / q_{t+1}$$

$$= \{\beta\{[\frac{1}{\lambda}(1-\beta) y_t^{\rho-1} A_{t-1} R_t - (1-\beta) y_t^{\rho}]/\beta\}^{(\rho-\alpha)/\rho} /[(1-\beta) y_t^{\rho-1}]\}$$
$$[\frac{1}{\lambda}(1-\beta) y_{t+1}^{\rho-1} A_t R_{t+1}]^{(\alpha-\rho)/\rho} (1-\beta) y_{t+1}^{\rho-1} q_t / q_{t+1}$$

$$= (\beta q_t / q_{t+1})^{\alpha/\rho} (y_t / y_{t+1})^{\alpha/\rho-\alpha} [(A_{t-1} R_t q_t - \lambda q_t y_t)/(A_t R_{t+1} q_{t+1})]^{(\rho-\alpha)/\rho}$$

Substituting equation (27) into equation (9a) and (9b) we get

(28a) $1 = E_t\{(\beta q_t / q_{t+1})^{\gamma}(y_{t+1} / y_t)^{\gamma(\rho-1)}[(A_{t-1}R_t q_t - \lambda q_t y_t)/(A_t R_{t+1} q_{t+1})]^{1-\gamma}(1+r_{t+1})\}$

(28b) $$p_{kt} + v_{kt} = E_t\{(\beta q_t / q_{t+1})^{\gamma}(y_{t+1} / y_t)^{\gamma(\rho-1)}[(A_{t-1}R_t q_t - \lambda q_t y_t)/(A_t R_{t+1} q_{t+1})]^{1-\gamma}$$
$$(\partial \pi_{t+1} / \partial a_{kt} + p_{k,t+1} + v_{k,t+1})\}$$

where $\gamma \equiv \alpha / \rho$

Rearrange equation (28a) and (28b) we get an estimable GMM moment functional form for our empirical model:

(29a) $U_{1t} = 1/q_t - (\beta q_t / q_{t+1})^{\gamma}(y_{t+1} / y_t)^{\gamma(\rho-1)}[(A_{t-1}R_t q_t - \lambda q_t y_t)/(A_t R_{t+1} q_{t+1})]^{1-\gamma}(1+r_{t+1})/q_t$

(29b) $$U_{2t} = p_t + v_t - (\beta q_t / q_{t+1})^{\gamma}(y_{t+1} / y_t)^{\gamma(\rho-1)}[(A_{t-1}R_t q_t - \lambda q_t y_t)/(A_t R_{t+1} q_{t+1})]^{1-\gamma}$$
$$(\partial \pi_{t+1} / \partial a_t + p_{t+1} + v_{t+1})$$

where $EU(\theta)'W = 0$

$v_t = c_p \Delta Q_t$ if $\Delta Q_t > 0$

$v_t = c_m \Delta Q_t$ if $\Delta Q_t < 0$

$\Delta Q_t = Q_t - Q_{t-1}$

Equation (29a) and (29b) are the two equations of our general homogeneity model, and all the variables used are defined as following:

- q_t : Consumer Price Index(1982~1984:1)

- y_t : disposable income of farm population ($trillion)
- R_t : gross rate of return on farm equity
- A_t : farm wealth levels (equity) ($100million)
- r_t : interest rate on U.S. treasury bills(%)
- p_t : Farm land price($100,000/acre)
- π_{t+1} / a_{kt} : net farm income per acre ($1000/acre)
- v_t : transaction costs of year t in farmland market
- Q_t : land quantity at time t

When we set λ to 1, equation (29a) and (29b) reduces to the linear homogeneity model:

(30a) $U_{1t} = 1/q_t - (\beta q_t / q_{t+1})^{\gamma} (y_{t+1} / y_t)^{\gamma(\rho-1)} (R_{t+1} q_{t+1})^{\gamma-1} (1 + r_{t+1}) / q_t$

(30b) $U_{2t} = p_t + v_t - (\beta q_t / q_{t+1})^{\gamma} (y_{t+1} / y_t)^{\gamma(\rho-1)} (R_{t+1} q_{t+1})^{\gamma-1} (\partial \pi_{t+1} / \partial a_t + p_{t+1} + v_{t+1})$

In spite of slight notation differences, our linear homogeneity model is the same as that of Model M1 in Chavas and Thomas (1999).

Data and Estimation

The above model is developed for a reprehensive consumer and we assume that all the functional forms would sustain with aggregated data. As defined in the equations, all the data are collected from USDA data set in 1950~2008 at US aggregated level.

The estimation methods and hypothesis tests are discussed in details in the Estimation Results section.

Estimation Results

2-stage GMM

Both the linear homogeneity model and the general homogeneity model are estimated with two-stage GMM procedure. Hansen (1992) shows that an asymptotically efficient or optimal GMM estimator of parameter vector could be obtained by choosing weight matrix so that it converges to the inverse of the long-run covariance matrix. In the first stage, we calculate an HAC – Newey-West weighting matrix, which is a heteroskedasticity and autocorrelation consistent estimator of the long-run covariance matrix based on an initial estimate of the parameter vector. First, we calculate the initial parameter estimates of the nonlinear system with two-stage least squares estimation by iterated convergence. Second, we use 2SLS estimates to obtain the residuals, and third, we obtain estimates of the long-run covariance matrix of the instrument-residual matrix, and use it to compute the optimal weighting matrix. In the second stage, we minimize the GMM objective function with the optimal weighting matrix obtained in stage 1 with respect to parameter vector. The non-linear optimization for the parameters iterates to convergence of 0.0001 and updates parameter estimates from the initial 2SLS estimates to the final 2-stage GMM estimates. Further, for the HAC procedure, we specify that the data is processed with prewhitening by VAR(1) and we choose Bartlett kernel and Newey-West bandwidth.

Instruments

In our two-stage GMM estimation, we use identical instrument vector for both equations in the system. In the linear homogeneity model, we estimate a five element parameter vector $(\rho, \gamma, \beta, C_m, C_p)$, with five different instruments (1, P_{t-1}, y_t/y_{t-1}, q_t/q_{t-1}, R_{t-1}). Since we have two equations in the linear homogeneity model, the real instrument number used is ten (two times five), which determines the degree of freedom of overidentifying test in our linear homogeneity model to be five, ten (number of instruments) minus five (number of parameters). Similarly, we estimate a six element parameter vector $(\rho, \gamma, \beta, C_m, C_p, \lambda)$, with seven different instruments (1, P_{t-1}, y_t/y_{t-1}, q_t/q_{t-1}, R_{t-1}, a_t , $Liability_t$) in our general homogeneity model. Therefore the degree of freedom of overidentifying test in our general homogeneity model is eight, fourteen (number of instruments) minus six (number of parameters).

Estimation

The GMM estimations are reported in Table 2 for both linear homogeneity model and general homogeneity model. Although estimations are basically consistent between two models, there are some very interesting differences.

First, the general homogeneity model yields a much higher estimate for ρ than the linear homogeneity model, which indicates that the intertemporal elasticity of substitution, $\sigma = 1/(1-\rho)$, is much higher under the general homogeneity model. The linear homogeneity model estimate for ρ is 0.754, and the corresponding intertemporal elasticity of substitution,

$\sigma = 1/(1-\rho)$, is 4.0650, very close to 4.10, the estimate of Chavas and Thomas (1999). However, the general homogeneity model estimate for ρ and σ are 0.9586 and 24.1546 respectively. This results show that agents in the farmland markets are even more flexible in income substitution between time periods than tradition C-CAMP predicts.

Second, the estimates of transaction cost parameters, Cp and Cm, in the linear homogeneity model are both insignificantly positive, which is close to the results from Chavas and Thomas (1999). The estimate of booming market transaction parameter, Cp, in the general homogeneity model is 0.1136 with standard error of 0.0568, positive and significant at 5% level, while that of the diminishing market, Cm, is -0.0074 with standard error of 0.0045, negative and marginally significant at 10% level. These results show that transaction costs, v_t, remain positive regardless the increasing or decreasing of farmland quantity. On one hand, the opposite signs of the transaction cost parameters in the general homogeneity model are more intuitive in line with the real world phenomenal. After all, both the buyers and sellers of farmland need to pay transaction costs, such as advertisements, research, legal fees, and so on. Therefore, it is reasonable to expect positive aggregated transaction costs in both booming and diminishing markets. On the other hand, these results eliminate transaction costs as one of the major drivers in the farmland market. Agents make decisions of buying or selling farmland always in presence of positive transaction costs, even though the magnitude of diminishing market parameter seems to be much smaller than that of the booming market. The magnitude difference is sensible because when the market is diminishing, agents become more cautious and this leads to an increase in market efficiency. The transaction amount decreases, and only the most economically efficient deals are closed in the market, which yields much lower transaction costs in aggregation. In short, the transaction costs affect farmland market, but not as significantly as a driving force.

Third, the general homogeneity model yields a much higher estimate for α than the linear homogeneity model, which indicates that the risk aversion coefficient of the farmland market participants could be much higher than the traditional model predicts, or farmers are much less risk averse than we thought. We follow Epstein and Zin (1991)'s definition of risk aversion coefficient: agents are risk neutral when their α=1, and become more risk averse when α decreases and vice versa. It is worth noticing that traditional time series models generate one single estimate of α in the whole period of study based on aggregated data. It is well documented that risk aversion could differ materially across different agent groups, according to elements such as age, income, education, health, and other geographical variables. In other words, the estimate of α is probably more like a baseline rather than a sensible average of agents' risk aversion coefficient. Even under the assumption of representative agent, the estimate of α needs extra cautions, because the risk aversion level for the same agents could change over time due to the changes of their geographical variables. It is apparent that other factor(s) should be included in the consideration of risk aversion in order to explain a certain year's land price data or to make a reasonable prediction of near future. In our general homogeneity model, we introduce wealth level, approximated by the farmers' equity, as a remedy to the embedded risk aversion coefficient misspecification problem in CAPM.

Fourth, and probably the most important, we find that the estimate of λ, homogeneity degree of consumption and value function, is 0.8277, with standard error of 0.0034. This finding is consistent with several previous assumptions we make about λ. First, λ is positive and significant, meaning that consumption is a valid increasing function of last period's wealth level, therefore, so is value function. In other words, this result provides empirical evidence to the hypotheses that agents' wealth level affects their future consumptions and utilities. Second, the magnitude of the estimate is between 0 and 2, showing that the nonlinear homogeneous function of $y_t(A_{t-1})$ could be closely approximated by a linear functional form as equation (16). This result reinforces the validity of our homogeneity test, which is derived from equation (18). Third, the estimate of λ is less than 1, indicating that our data better support a nonlinear rather than a linear homogenous functional form of consumption. This also illustrates the necessity of a general homogeneity model in farmland pricing.

In addition, the objective function value, reported as J-stat, are low for both models: 0.1085 for linear homogeneity model and 0.2460 for general homogeneity model. The estimates for γ and β are both close to 1 in both models, and they are consistent with the findings of Chavas and Thomas (1999). The R-squared are close between the linear homogeneity model and general homogeneity model, but they are both significantly lower than that of Chavas and Thomas (1999), which could be caused by the persistent farmland price rise since 1997, and especially the sharp rise since 2004. The general homogeneity model has a slightly higher R-squared in equation (29b), 0.3350 than its counterpart, 0.2345, in the linear homogeneity model (30b), meaning that the general homogeneity assumption helps to explain the variance in US farmland prices. This result is intuitive since we add one more parameter: λ, homogeneity degree of consumption, to estimate in equation (29b), whose estimate turns out to be significantly different from 1, which unsurprisingly increases the explanation power of the general homogeneity model in farmland pricing.

Hypothesis testing

The GMM estimates are tested and results are reported in Table 4 for both linear homogeneity model and general homogeneity model. Both models pass the over identification test with very high p-values, supporting the overall validity of the instrument variables. With insignificant parameter estimates, the linear homogeneity model fails to reject both the No transaction costs hypotheses and the Symmetric transaction costs hypotheses, while the general homogeneity model estimates reject the No transaction cost hypotheses at 1% level and reject the Symmetric transaction costs hypotheses at 5% level. In other words, US farmland data do not provide evidence against the No transaction costs hypotheses in 1950~2008 period as Chavas and Thomas find in the 1950~1996 period with the linear homogeneity model.

As to the expected utility hypotheses, the linear homogeneity model fails to reject the null: (γ =1), while the general homogeneity model shows that γ is close to but statistically bigger than 1. Both models provide evidence of the advantage of "consumption smoothing" over "income smoothing" in the effects of risk aversion. The almost-equal-to-1 γ estimates are both in favor of the dynamic consumption-based CAPM model. The difference is that the linear homogeneity model shows that the estimate of ρ is not statistically different from that of α, while the general homogeneity model indicates that α is close to but bigger than ρ, which provide empirical evidence against the traditional expected time-additive utility specification.

ρ and α are both found significantly different from 1 at 1% level by Chavas and Thomas (1999) with the linear homogeneity model. In our GMM estimation, ρ is significantly different from 1 at 1% level, and α is marginally different from 1 at 10% in the linear homogeneity model, and both insignificantly different from 1 in the general homogeneity model. A possible explanation is that with the highly aggregated data, the estimations of intensively preference related variables such as intertemporal elasticity of substitution and risk aversion coefficient could be interpreted as a boundary or frontier of individual or subgroup observation values rather than the average of them.

Our linear homogeneity model estimation fails to reject the 0 rate of time preference hypotheses null (β =1) as Chavas and Thomas (1999) did. But the general homogeneity model estimates find strong evidence against 0 rate of time preference: Chi-square= 147.7758 and p-value=0.0000, which is consistent with Chavas and Thomas (1999).

A last hypothesis testing reported in Table 4 is the linear homogeneity test for our general homogeneity model. The null hypothesis is that λ =1 or the consumption is a linear homogeneity function of previous wealth level. The chi-square statistics is 2518, indicating that homogeneity degree of consumption is significantly less than 1. This test supports the necessity of general homogeneity model and helps to explain the better performance of the general homogeneity model comparing to the linear homogeneity model.

Homogeneity Test

Both the linear homogeneity model and the general homogeneity model are built on the assumption A2: consumption y_t is a homogeneous function of previous wealth level A_{t-1}. It is important to check if this assumption is supported by data used for estimation in both models to verify the specification of the functional forms and therefore the validity of the parameter estimations.

From equation (18), we define that

Delta=left side –right side

$$= \left[\frac{R_t q_t}{\lambda} - (r_t + 1) + \frac{a_{0t}}{a_{0,t-1}}\right]$$

$$- \sum_{k=1}^{K} \frac{a_{kt-1}}{a_{0t-1}} \left[\frac{\partial \pi_t}{\partial a_{kt-1}} + (P_{kt} + v_{kt})\left(1 - \frac{a_{kt}}{a_{k,t-1}}\right) - \frac{R_t q_t}{\lambda}(P_{kt} + v_{kt})\right]$$

It is obvious that Delta should be close to 0 if the homogeneity assumption holds; otherwise it indicates that data used in estimation do not support homogeneity at the estimated degree.

Figure 1 shows the calculated Delta values for both linear and nonlinear (general) homogeneity model. As we can see, the nonlinear homogeneity model with degree of 0.8277 yields delta values ranging from -0.5 to 1.2, which is acceptable considering the noises in data and errors in estimation. However, the linear homogeneity model yields delta values ranging from 1 to 24.5, suggesting that US farm data fail to support the linear homogeneity assumption.

Robustness

In order to further explore the validity of our general homogeneity model, we also estimate it with full information Maximum Likelihood and 3 Stage Least Squares. Table 3 demonstrates the estimations of general homogeneity model with all 3 methods: GMM, ML, and 3SLS. Out of total seven parameters estimated, the magnitude and significance level for six parameters are stable across all 3 methods, and the only difference is that the estimates of parameter for transaction cost in booming market are insignificant with ML and 3SLS, but significantly positive at 5% level with GMM.

These results indicate that our estimates of the general homogeneity model are not sensitive to estimation methods. The functional forms adopted in the estimation are reasonable and robust against structural misspecifications, while the estimates are reliable and useful in predictions.

Predictability

To test the reliability of out-of-sample predictions of our models, we perform recursive predictions with both linear homogeneity model and general homogeneity model, and compare them with the true data of farmland prices during 1997~2008. The recursive predictions are made through a repeated procedure. First we use all the data from year 1950 to year n to obtain GMM estimations $(\rho, \gamma, \widehat{\beta, C_m}, C_p, \lambda)_n$ of a model, and we use $(\rho, \gamma, \widehat{\beta, C_m}, C_p, \lambda)_n$ and data needed in the functional form (b) to predict p_{n+1}, the farmland price of year n+1. Then we repeat this procedure for year n+1 to predict the farmland price in year n+2, and so on.

Figure 2 shows the comparison results of linear homogeneity model and general homogeneity model with observed value of farmland price from 1997 to 2008. As we can see, among all 12 years' predictions, the general homogeneity model always performs better than the linear homogeneity model because the nonlinear predictions are always closer to the observed values than the linear predictions. Except for four years: 1998, 2003, 2004, and 2007, when the two predictions are close, the nonlinear predictions are significantly higher than the linear predictions, which helps to explain the alleged farmland overpricing puzzle.

This result is also consistent with the higher R-squared for the general homogeneity model when compared to the linear homogeneity model. Both results illustrate that the general homogeneity model has stronger explanatory power and more reliable predictability in farmland pricing.

Conclusions

In the article, we develop a general homogeneity model to enhance model robustness against risk aversion coefficient misspecification in the traditional C-CAPM model. We find that US farmland data support a nonlinear functional form rather than a linear form for consumption. We also find that both farmland returns and consumers' wealth levels are determinates for farmland assets value. Our model generates better out-of-sample predictions and our results are robust to estimation methods. It provides empirical evidence of the effects of transaction costs and risk aversion on farmland prices.

References

1. Arrow, KJ., 1965, “Uncertainty and the welfare economics of medical-care.” American economic review 55 (1): 154-158

2. Alston, J.M. (1986) “An Analysis of Growth of U.S. Farmland Prices. 196342” *Amen can Journal ofAgricuLturai Economics* 68(1): 1—9.

3. Barry, P.J., L.J. Robison, and G.V. Neartea. “Changing Time Attitudes in Intertemporal Analysis.” Amer. J. Agr. Econ. 78(November 1996):972-81.

4. Burt, O. (1986) “Econometric Modeling of the Capitalization Formula for Farmland Prices.” *American Journal ofAgnicultural Economics* 68(1): 10—26.

5. Campbell. J.Y. and Ri. Shiller. (1987) “Cointegration and Tests of Present Vaiuc Models.” *Journal of Political Economy* 95(5): 106248.

6. Chavas, JP and Thomas, A., 1999, “A dynamic analysis of land prices.” American Journal of Agricultural Economics, Vol. 81, No. 4, pp. 772-784

7. Chavas, J.P. (2003)

8. Clark. J,S.. M. Fulton. and J.T. Scott. Jr. (1993) “‘The Inconsistency of Land Values. Land Rents, and Capitalization Formulas.” *American Journal of Agricultural Economics* 75(l): 147—55.

9. Epstein, L.G., and S.E. Zin. “Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework.” Econometrica 57(July 1989):937-69.

10. Epstein, L.G., and S.E. Zin. “Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: An Empirical Analysis.” J. Polit. Econ. 99(April 1991):263-86.

11. Falk. B. (1991) “Formally Testing the Present Value Model of Farmland Prices.” *American Journal of Agricultural Economics* 73(1): 1—10.

12. Falk, B. and B.S. Lee. (1998) “Fads versus Fundamentals in Farmland *Prices.” A,nerican Journal of Agricultural Economics* 80(4): 696—707.

13. Featherstone, AM. and TO. Baker. (1987) “An Examination of Farm Sector Real Estate Dynamics: 1910-85.” *American Journal ofAgriculsural Economics* 69(3): 532-46.

14. Flavin, MA. (1983) “Excess Volatility in the Financial Markets: A Reassessment of the Empirical Evidence.” *Journal of Political Economy* 9 1(6): 929—56.

15. Fontnouvelle, Patrick de and Sergio H. Lence, “Transaction Costs and the Present Value "Puzzle" of Farmland Prices” *Southern Economic Journal*, Vol. 68, No. 3 (Jan., 2002), pp. 549-565

16. Gómez-Limón, José A., Arriaza, Manuel, and Riesgo, Laura, 2002, “An MCDM analysis of agricultural risk aversion.” European Journal of Operational Research Vol. 151, Issue 3, pp. 569-585

17. Hanson, S.D., and R.J. Myers. “Testing for a Time-Varying Risk Premium in the Returns to U.S. Farmland.” J. Emp. Financ. 2(September 1995):265-76.

18. Irwin, S.H. and R.L Coiling. (1990) “Are Farm Asset Values Too Volatile” *Agricultural Finance Review* 50(l): 58—65.

19. Just, Richard E. and Miranowski, John A., 1993, “Understanding farmland price changes.” American Journal of Agricultural Economics, Vol. 75, No. 1, pp. 156-168

20. Kleidon. A.W. (1986) “Variance Bounds Tests and Stock Price Valuation Models.” *Journal of Political Economy* 94(5): 953—1001.

21. Kocherlakota, N.R. (1996) “The Equity Premium: It’s Still a *Puzzle.” Journal of &o. nomic Literature* 34(1): 42—71.

22. Lee. B.S. _ (1998) “Permanent, Temporary, and Non-Fundamernal Components of Stock Prices.” *Journal of Financial and Quantitative Analysis* 33(l): 1—32.

23. Lcncc. S.H. (2001) “Farmland Prices in the Presence of Transaction Costs: A Cautionary Note.”

24. Lcncc. S.H. (2003)

25. Lence, S.H. and Di. Miller. (1999) ‘l’ransacuons Costs and the Present-Value Model of Farmland: Iowa. 1900-94.” *American Journal of Agricultural Economics* 8 1(2): *257—*72.

26. LeRoy. S.F. and R.D. Porter. (1981) “The Present Value Relation: Tests Based on Implied Variance Bounds.” *Eonomerrica* 49(3): *555—74.*

27. Miller, D.J. (2003)

28. Moss, Charles B. and Katchova, Ani L., 2005, “Farmland valuation and asset performance.” Agricultural Finance Review Vol. 65, Issue: 2, pp.119 – 130

29. Plantinga, Andrew J., Ruben N. Lubowski, ,and Robert N. Stavin, 2002, “The effects of potential land development on agricultural land prices” Journal of Urban Economics 52 (2002) 561–581

30. Pratt, John W., 1964, “Risk Aversion in the Small and in the Large.” Econometrica, Vol. 32, No. 1/2, pp. 122-136

31. Schmitz. A. (1995) “Boom-Bust Cycles and Ricardian RenL” *American Journal of Agricultural Economics* 77(5): 1110—25.

32. Shiller, Ri. (1981) “Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends’” *American Economic Review* 7 1(3): 421—36.

33. Shiha, A.N., and J.P. Chavas. “Capital Segmentation and U.S. Farm Real Estate Pricing.” Amer. J. Agr. Econ. 77(May 1995):397-407.

34. Turvey, Calum, 2002, “Can hysteresis and real options explain the farmland valuation puzzle?” WORKING PAPER 02/11

http://ageconsearch.umn.edu/bitstream/34131/1/wp0211.pdf

Table 1. Descriptive Statistics, 1950-2008

Variable	Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis	Autocorrelation Coefficient
q_t(= 1 in 1982-84)	0.9121	0.6154	0.2410	2.1530	0.4794	-1.2501	0.9996
y_t(billion dollars)	69.2605	16.0702	41.9507	123.3692	0.9209	1.3116	0.8146
Q_t (million acres)	1056.0200	94.6592	919.9000	1206.3550	0.2190	-1.3532	0.9993
p_t (1,000 $/acres)	0.5945	0.5087	0.0650	2.1700	1.1522	1.1551	0.9959
a_t (billion dollars)	605.1680	448.2733	151.9045	1841.2120	0.9933	0.5685	0.9939
R_t	1.1597	0.0734	0.9599	1.4166	0.0929	2.6367	0.6270
π_t/a_t (1,000 $/acre)	0.0313	0.0229	0.0091	0.0947	1.0584	0.4011	0.9260
r_t	0.0509	0.0264	0.0092	0.1316	0.7596	0.5695	0.8809

Note: Number of observations is 59.

Table 2. GMM Estimation Results, 1950-2008

	Linear Homogeneity			General Homogeneity		
	Estimate	Std. Error	t-Ratio	Estimate	Std. Error	t-Ratio
ρ	0.7547	0.0807	9.3482	0.9586	0.0429	22.3410
γ	0.9701	0.1115	8.6969	1.0185	0.0038	267.6441
β	0.9726	0.1279	7.6027	0.9558	0.0051	186.3042
c_m	0.0084	0.0145	0.5814	-0.0074	0.0045	-1.6315
c_p	0.2062	0.2318	0.8895	0.1136	0.0568	2.0008
α	0.7321	0.1323	5.5316	0.9763	0.0423	23.0554
λ	Set to 1	-	-	0.8277	0.0034	241.1212
J-stat	0.1085			0.2460		
R^2 equation (a)	0.5174			0.5010		
R^2 equation (b)	0.2345			0.3350		

Note: The t-ratios are obtained under the null Ho: $\beta = 0$. The Linear Homogeneity parameters are estimated from equations (30a) and (30b), while the General Homogeneity parameters are estimated from equations (29a) and (29b).

Table 3. GMM, ML, and 3SLS Estimations for General Homogeneity Model, 1950-2008

	GMM			ML			3SLS		
	Estimate	Std. Error	Wald-Stat	Estimate	Std. Error	Wald-Stat	Estimate	Std. Error	Wald-Stat
ρ	0.9586	0.0429	497.5111	0.9802	0.0164	3555.4680	0.9566	0.1168	66.8666
γ	1.0185	0.0038	71633.3834	0.9994	0.0028	126495.9	1.0153	0.0105	9301.2505
β	0.9558	0.0051	33405.0900	0.9807	0.0063	24616.1600	0.9479	0.0193	2419.7650
c_m	-0.0074	0.0045	2.6616	-0.0003	0.0035	0.0077	-0.0226	0.0201	1.2623
c_p	0.1136	0.0568	4.0033	0.0142	0.3551	0.0016	-0.0604	0.1887	0.1025
α	0.9763	0.0423	529.8373	0.9796	0.0168	3398.8210	0.9712	0.1196	65.7352
λ	0.8277	0.0034	58139.4400	0.8286	0.0000	1.45E+27	0.8280	0.0065	16136.9487

Note: For the Wald tests the critical values of $x^2{}_{(1)}$ are 2.71, 3.84, 6.63, and 10.83 for a 10%, 5%, 1%, and 0.1% significance level, respectively. All three estimations are obtained from equations (29a) and (29b).

Table 4. Hypothesis Testing, 1950-2008

		Linear Homogeneity		*General Homogeneity*	
		Test Statistic	p-Value	Test Statistic	p-Value
Overidentifying restrictions	(Hansen test)	$x^2(5) = 0.1085$	0.9998	$x^2(8) = 0.2460$	0.9999
No transaction costs	$(c_p = c_m = 0)$	$x^2(2) = 1.0923$	0.5792	$x^2(2) = 13.8794$	0.0010
Symmetric transaction costs	$(c_p = c_m)$	$x^2(1) = 0.7284$	0.3934	$x^2(1) = 4.9195$	0.0266
Expected utility	$(\gamma = 1)$	$x^2(1) = 0.0718$	0.7887	$x^2(1) = 23.5875$	0.0000
Infinite intertemporal elasticity of substitution	$(\rho = 1)$	$x^2(1) = 8.1808$	0.0042	$x^2(1) = 1.0028$	0.3166
0 rate of time preference	$(\beta = 1)$	$x^2(1) = 0.0007$	0.9790	$x^2(1) = 147.7758$	0.0000
Risk neutrality	$(\alpha = 1)$	$x^2(1) = 3.6801$	0.0551	$x^2(1) = 0.3564$	0.5505
Linear Homogeneity	$(\lambda = 1)$	$x^2(1) =$	-	$x^2(1) = 2518.3218$	0.0000

Note: The Linear Homogeneity parameters are estimated from equations (30a) and (30b), while the General Homogeneity parameters are estimated from equations (29a) and (29b).

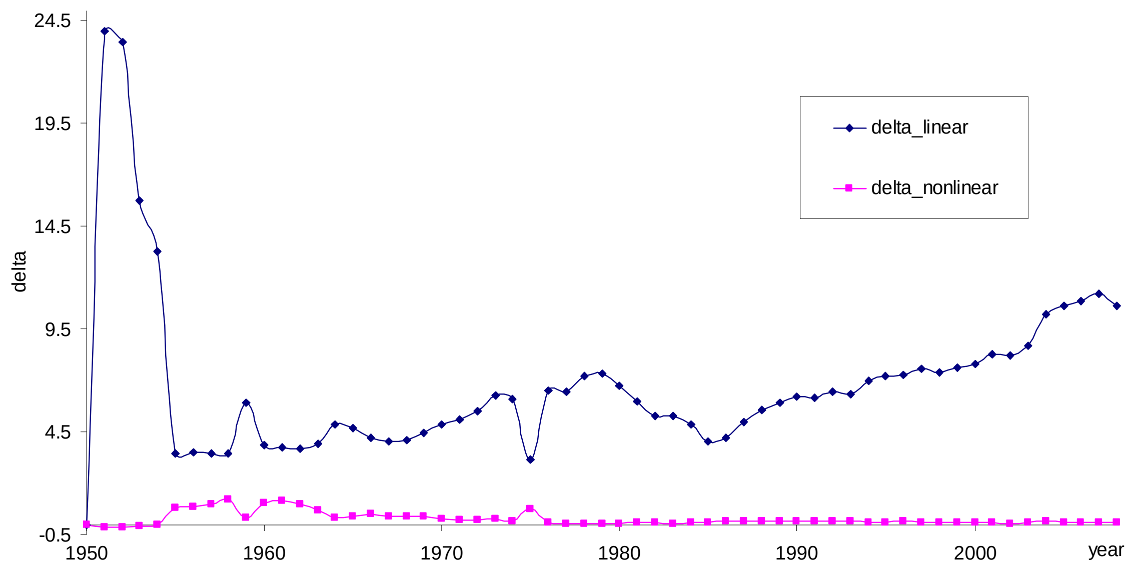

Figure 1. Homogeneity Test for Linear Homogeneity Model and General Homogeneity Model

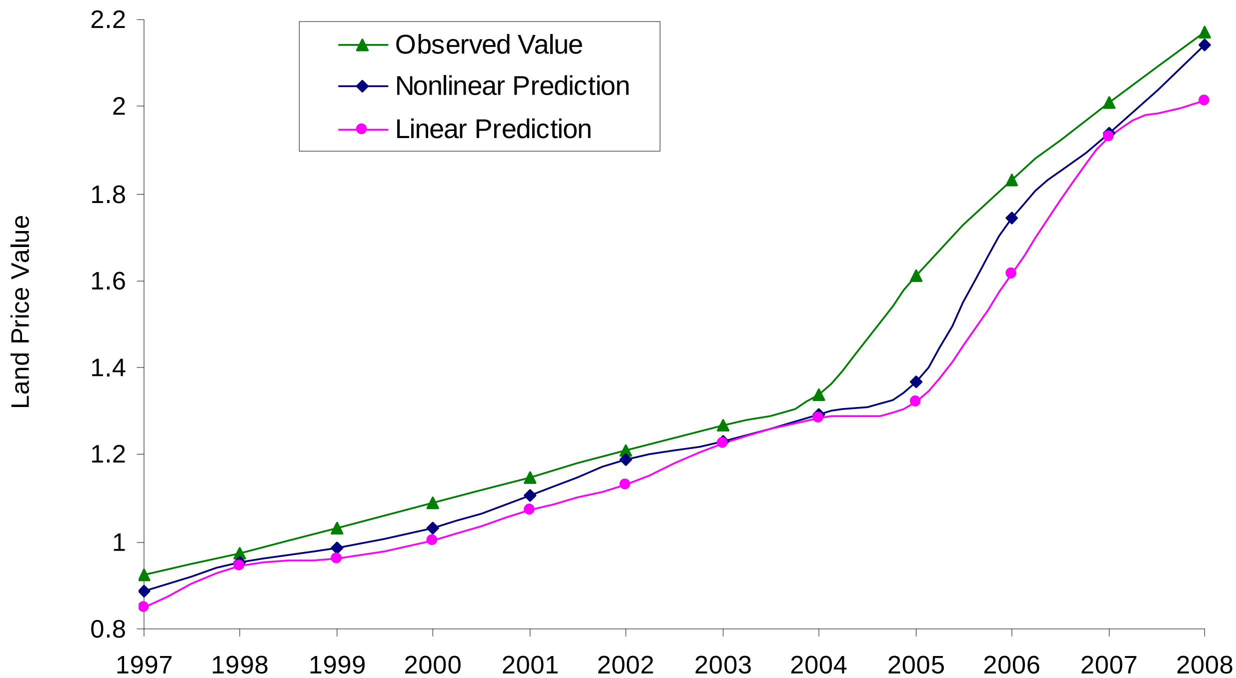

Figure 2. Prediction Comparison for Linear Homogeneity Model and General Homogeneity Model