

ESSAYS IN FINANCIAL ECONOMETRIC INVESTIGATIONS OF FARMLAND
VALUATIONS

A Dissertation

by

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ABSTRACT

This dissertation consists of three essays wherein tools of financial econometrics are used to study the three aspects of farmland valuation puzzle: short-term boom-bust cycles, overpricing of farmland, and inconclusive effects of direct government payments.

Essay I addresses the causes of unexplained short-term boom-bust cycles in farmland values in a dynamic land pricing model (DLPM). The analysis finds that gross return rate of farmland asset decreases as the farmland asset level increases, and that the diminishing return function of farmland asset contributes to the boom-bust cycles in farmland values. Furthermore, it is mathematically proved that land values are potentially unstable under diminishing return functions. We also find that intertemporal elasticity of substitution, risk aversion, and transaction costs are important determinants of farmland asset values.

Essay II examines the apparent overpricing of farmland by decomposing the forecast error variance of farmland prices into forward looking and backward looking components. The analysis finds that in the short run, the forward looking Capital Asset Pricing Model (CAPM) portion of the forecast errors are significantly higher in a boom or bust stage than in a stable stage. This shows that the farmland market absorbs economic information in a discriminative manner according to the stability of the market, and the market (and actors therein) responds to new information gradually as suggested by the theory. This helps to explain the overpricing of farmland, but this explanation works primarily in the short run.

Finally, essay III investigates the dual effects of direct government payments and climate change on farmland values. This study uses a smooth coefficient semi-parametric panel data model. The analysis finds that land valuation is affected by climate change and government payments, both through discounted revenues and through effects on the risk aversion of land owners. This essay shows that including heterogeneous risk aversion is an efficient way to mitigate the impacts of misspecifications in a DLPM, and that precipitation is a good explanatory variable. In particular, precipitation affects land values in a bimodal manner, indicating that farmland prices could have multiple peaks in precipitation due to adaption through crop selection and technology alternation.

DEDICATION

To my family, for their love and support

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NOMENCLATURE

2SLS	Two-Stage Least Squares
ACRE	Average Crop Revenue Election
ARPs	Acreage Reduction Programs
CAPM	Capital Asset Pricing Models
C-CAPM	Consumption-Capital Asset Pricing Models
CCPs	Counter-Cyclical Payments
CRP	Conservation Reserve Program
CSP	Conservation Stewardship Program
DAG	Directed Acyclic Graph
DCP	Direct and Counter-Cyclical Programs
DGP	Direct Government Payments
DLPM	Dynamic Land Price Model
DPs	Direct Payments
EQIP	Environmental Quality Incentives Program
FEVD	Forecast Error Variance Decomposition
GES	Greedy Equivalent Search
GLS	Generalized Least Squares
GMM	General Method of Moments
GP	Government Payments
IPCC	Intergovernmental Panel on Climate Change

LDPs	Loan Deficiency Payments
MLGs	Marketing Loan Gains
OLS	Ordinary Least Squares
PFC	Production Flexibility Contract
QRE	Quasi-Rational Expectation
RAC	Risk Aversion Coefficient
RE	Rational Expectations
RGui	R General User Interface
RMSE	Root Mean Squared Errors
RW	Random Walk
SUR	Seemly Unrelated Regression
USDA	U.S. Department of Agriculture
USDL	U.S. Bureau of Labor Statistics
VAR	Vector Auto Regression
SUR	Seemly Unrelated Regression

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CHAPTER I

INTRODUCTION

Although U.S. farmland values have been studied with numerous land pricing models, a farmland valuation puzzle 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 the 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. However, in the short run farmland prices diverge significantly away from the discounted value, and these short-run divergent periods are referred to as boom or bust cycles. Furthermore, a number of studies report the overreaction of farmland values in response to increases in returns (Featherstone and Baker 1987; Irwin and Coiling 1990; Falk 1991; Clark, Fulton, and Scott Jr 1993; Schmitz 1995).

Second, while the directions of changes in farmland values are consistent with the capitalization formula, farmland appears to be systematically overpriced. Farmland returns are considered too low relative to farmland values, compared with other sectors in the capital market in a capital asset pricing model context (Moss and Katchova 2005).

Third, existing literature has not provided a closure of the effects of direct government payments on farmland prices. Direct government payments are found to be positively and negatively related to farmland prices in different studies.

Farmland values make up 84 percent of U.S. agriculture assets; therefore the farmland valuation puzzle is an important issue that has stimulated substantial researches. 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; Lence 2001). Researchers have also explored potential arbitrage barriers for overpriced farmland values, such as the absence of short selling and transaction costs (Chavas 2008; Lence and Mishra 2003).

Some studies have tried to understand land values and their fluctuations based on market fundamentals. Irwin and Coiling (1990) used 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 found that the variability in the returns was potentially larger than that implied by the variability of farmland prices, but this methodology may have suffered from nonstationarity (Kleidon 1986) and small-sample bias (Flavin 1983). Campbell and Shiller (1987) developed the test of the present-value model to deal with nonstationary data. Falk (1991) used Campbell and Shiller's (1987) approach to see if there was a stationary relationship

between farmland values and returns to farmland but did not find one. Hanson and Myers (1995) find that some variation in farmland values can be explained by a time-varying-discount rate.

Falk and Lee (1998) found that fads and overreactions are relevant to short-run pricing behavior, while permanent fundamentals cause long-run price movements. Barry, Robison, and Neartea (1996) allowed for the effects of risk and risk aversion on asset prices, and found that increasing time attitudes are comparable to the Arrow-Pratt measures of risk attitudes. Shiha and Chavas (1995) found that transaction costs have significant effects on land prices. Epstein and Zin (1991) found 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) found that inflation-rate and real returns on alternative uses of capital may cause changes in farmland values.

Chavas and Thomas (1999) found risk aversion and transaction costs are important determinants of farmland prices. Lence (2001) cautioned about the effects of data non-stationarity in the Just and Miranowski (1993) and the deduction in Chavas and Thomas (1999) studies. Plantinga, Ruben, and Robert (2002) decomposed agricultural land values into components reflecting the discounted value of future land development and the discounted value of agricultural production, and found that those components explain 91% of the overall level of US farmland values. De Fontnouvelle and Lence (2002) found robust evidence that the behavior of land prices and rents is consistent with

the constant-discount-rate present-value-model (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, including the effects of direct government payments.

This dissertation consists of three essays studying the three aspects of farmland valuation puzzle. Essay I addresses causes of the short-term boom-bust cycles in farmland values, which are not explained by the classic asset value formulations. Essay II addresses the apparently overpriced farmland value by decomposing the variance of forecast errors in CAPM (forward) portion and Random Walk (backward) portion. Essay III investigates the effects of direct government payments (DGP) and climate change on farmland values, shedding some new light on the contribution of those factors.

CHAPTER II

ASSET RETURNS AND BOOM-BUST CYCLES IN FARMLAND PRICES

The value of farm real estate, including land and structures, constitutes 84 percent of the 2009 total value of U.S. farm assets (Nickerson et al 2012). Since farmland is a big part of farmers' wealth and an important business to banks that finance farming operations, changes in agricultural land values are an essential economic issue. This chapter endeavors to explain boom-bust cycles in farmland prices with a general, instead of linear, homogeneous return function of farmland assets. A dynamic land pricing model (DLPM) is estimated over U.S. farmland data under alternative assumptions of the budget constraint.

2.1. Background

In this essay we refer to the boom-bust cycles of land prices following Schmitz (1995). We define the boom stage as the case when the farmland prices are persistently higher than those implied by the present value of earnings. The bust stage is one where the valuation is persistently lower than the present value, and the other cases are the stable stage (Falk 1991).

Chavas and Thomas (1999) followed Epstein and Zin (1991) and developed a DLPM that incorporates risk aversion, transaction costs, and dynamic preferences. They applied this model to 1950-1996 U.S. farmland values, and found that risk aversion and transaction costs are important determinants of farmland prices. But they made some

strong assumptions in their analysis. In particular, they assumed linear homogeneity of the underlying budget constraint and the associated profit function.

The objective of this essay is to contribute to the explanation of boom-bust cycles using US farmland data under the general homogenous functional forms of farmland return. In this essay, we extend the work of Chavas and Thomas (1999) by relaxing an essential assumption of the budget constraint. We assume a farmland return function of general, instead of linear, homogeneous functional forms. The general homogenous functional form is a relaxation of the usual case covered in existing literature of dynamic CAPM.

We expect our empirical results to be consistent with the major findings of the existing capitalization formula. First, we correct the undersized error terms of our 2-stage General Method of Moments (GMM) estimation by Windmeijer' general function formula (2005). Second, we compare the restricted and unrestricted models. We expect that the linear (restricted homogeneity degree of 1) estimation of risk aversion coefficient is significantly lower than that of the general (unrestricted) model, which helps to explain the apparently overpriced farmland through risk aversion misspecifications in traditional DLPM. As we know, if the risk aversion is over estimated, the price according to that risk aversion will be under estimated. Third, we test the hypothesized nonlinear homogeneous relationship between farmland return and wealth level in our model with US data, and expect a significantly nonlinear relationship. Last, we expect better out of sample predictions from the general homogeneity model.

Our DLPM framework provides a platform for further studies on boom-bust cycles in farmland prices.

The remainder of the essay is organized as follows: 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 empirical results. Section V summarizes and concludes the essay.

2.2. The Model

2.2.1. Model Development

We build our model based on the widely used Consumption-Capital Asset Pricing Model (C-CAPM). Following Gregory Mankiw and Shapiro (1986), we consider a representative agent facing an optimization problem. His goal is to maximize his utility through his choices of levels of consumption and allocation of his portfolio among various assets each period. At period t , the agent has the option to consume y_t and invest m_t . Under the assumption of rationality, the agent maximizes utility through consumption and investment decisions. We assume that the agent's budget constraint is binding and denoted as follows:

$$r_t a_{0,t-1} + \pi_t(a_{1,t-1}, \dots, a_{J,t-1}) = q_t y_t + m_{0t} + \sum_{j=1}^J [P_{jt} + v_{jt}(m_{jt})] m_{jt} \quad (2.1)$$

where $m_{jt} = a_{j,t} - a_{j,t-1}$, $j = 0, 1, 2, \dots, J$. At period t , the agent's assets, $a_t = (a_{0,t}, a_{1,t}, \dots, a_{J,t})$, consist of two parts: a riskless asset, $a_{0,t}$, and risky assets, $(a_{1,t}, \dots, a_{J,t})$. r_t is the return rate for the riskless asset, and $\pi_t()$ is a first order differentiable return function for risky assets. The new investments of assets in period t

are denoted as $m_t = (m_{0,t}, m_{1,t}, \dots, m_{J,t})$, and they make up the changes between the asset levels in period t and $t-1$. q_t is the market price of consumption good y_t , P_{jt} is the market price for asset j , and v_{jt} represents the unit transaction cost of buying or selling asset j at period t . equation (2.1) states that the total returns from riskless and risky assets are allocated between the consumption, $q_t y_t$, and new asset investments, $m_{0t} + \sum_{j=1}^J [P_{jt} + v_{jt}(m_{jt})]m_{jt}$, for a utility maximizing agent.

Now we consider three scenarios for the transaction cost function $v_{jt}(m_{jt})$:

$$\begin{aligned} v_{jt}(m_{jt}) &= v_j^+ > 0 \quad \text{if } m_{jt} > 0, \\ &= 0 \quad \text{if } m_{jt} = 0, \\ &= v_j^- > 0 \quad \text{if } m_{jt} < 0 \end{aligned} \tag{2.2}$$

Suppose that both the buyers and sellers have to pay a positive fee to third parties in order to close the deal, therefore both v_j^+ , the transaction cost for buying, and v_j^- , the transaction cost for selling, are positive although they may not be the same. This transaction cost structure reflects a situation where transaction costs reduce the income of all market participants and discourages them from participation.

Following Epstein and Zin (1991) and Chavas and Thomas (1999), we assume a recursive utility framework:

$$U_t = [(1 - \beta)y_t^\rho + \beta M_t^\rho]^\frac{1}{\rho} \tag{2.3}$$

where $M_t = M(U_{t+1}|I_t) = (E_t U_{t+1}^\alpha)^\frac{1}{\alpha}$. y_t is the agent's consumption at period t , and E_t is the expectation operator based on the information available at time t . $\delta = (1 - \beta)/\beta$ is the rate of time preference, and $\sigma = 1/(1 - \rho)$ is the intertemporal elasticity of

substitution. The relative risk aversion coefficient $RAC = -\frac{M''_t(U_{t+1})}{M'_t(U_{t+1})}U_{t+1} = (1 - \alpha)(\frac{E_t[U_{t+1}^{\alpha-2}]}{E_t[U_{t+1}^{\alpha-1}]} - \frac{E_t[U_{t+1}^{\alpha-1}]}{E_t[U_{t+1}^{\alpha}]})U_{t+1}$ is a decreasing function of α .

2.2.2. Specifications

Equations (2.1), (2.2), and (2.3) have established the basic structure of budget constraint and utility function of the representative agent. In this section, we further specify the optimization problem and derive a first order condition system of equations that can be estimated with observable data. We will then discuss the homogeneity condition of gross returns with respect to asset holdings.

We define the representative agent's asset level at period t as A_t :

$$A_t = a_{0t} + \sum_{j=1}^J (P_{jt} + v_{jt})a_{jt} \quad (2.4)$$

Define the gross return at time t as

$G_t = (1 + r_t)a_{0,t-1} + \pi_t(a_{1,t-1}, \dots, a_{J,t-1}) + \sum_{j=1}^J [P_{jt} + v_{jt}]a_{j,t-1}$, and the gross rate of return on wealth at time t as

$$R_t = G_t/A_{t-1}.$$

Then the budget constraint expressed in equation (2.1) can be alternatively written as

$$A_t + q_t y_t = R_t A_{t-1} \quad (2.5)$$

Assume gross return G_t is homogeneous degree of λ in A_{t-1} ,

$$G_t = A_{t-1}^\lambda K_t \quad (2.6)$$

where K_t is exogenous.

Then by the definition of R_t , we have

$$A_{t-1}R_t = A_{t-1}^\lambda K_t$$

$$\Rightarrow R_t = A_{t-1}^{\lambda-1} K_t \quad (2.7)$$

It is generally the case in the land valuation literature to assume the value of λ is 1 (Chavas and Thomas 1999). Here we relax this assumption, and discuss three scenarios of return functions according to the range of the homogeneity degree parameter λ .

First, when the gross return G_t is linear and homogeneous in A_{t-1} , the homogeneity degree parameter λ equals 1. In turn equation (2.7) reduces to the commonly used "exogenous gross return rate" assumption, $R_t = K_t$. That is, the representative agent has an exogenous gross return rate. Therefore the gross return is proportional to the investment asset level, which implies an economy with a linear return function.

Second, when the homogeneity degree parameter falls between zero and one ($0 < \lambda < 1$), then the gross return rate gets smaller as the invested asset level gets larger, which is the characteristic of a concave return function of the economy, which is probably the results of diminishing returns to land as use expands likely due to land quality. This scenario has some interesting implications in the real world asset pricing phenomenon. For instance, in the case of bubbles, as the invested asset level gets higher, the economy gets bigger but less efficient, which would explain a smaller gross return rate in the farm sector.

Third, when the homogeneity degree parameter λ is greater than 1, the gross return rate gets bigger as the invested asset level grows, which is the characteristic of a convex return function of the economy. Here we model the return function with

homogeneity, which is a simplification. In fact, the return function could be heterogeneous.

To simplify notation, we define $\dot{U}_t \equiv \frac{U_t^\rho}{1-\beta}$ and $\gamma \equiv \alpha/\rho$, then we have

$$\begin{aligned} M_t^\rho &= (1 - \beta)(E_t \dot{U}_{t+1}^\gamma)^{1/\gamma} \\ \Rightarrow \dot{U}_t &= y_t^\rho + \beta(E_t \dot{U}_{t+1}^\gamma)^{1/\gamma} \end{aligned} \quad (2.8)$$

Since $\max \dot{U}_t$ is equivalent to $\max U_t$, given $\rho > 0$ and $\beta < 1$, the original optimization problem expressed in equation (2.3) is transformed into the following:

$$\max \dot{U}_t = y_t^\rho + \beta(E_t \dot{U}_{t+1}^\gamma)^{1/\gamma} \quad (2.9)$$

where $\rho > 0$ and $\beta < 1$

The first order conditions with respect to consumption y_t , riskless asset a_{0t} , and risky asset a_{jt} are

$$\frac{\partial(y_t^\rho)}{\partial y_t} + \beta \frac{\partial(E_t \dot{U}_{t+1}^\gamma)^{1/\gamma}}{\partial y_t} = 0 \quad (2.10a)$$

$$\frac{\partial(y_t^\rho)}{\partial a_{0t}} + \beta \frac{\partial(E_t \dot{U}_{t+1}^\gamma)^{1/\gamma}}{\partial a_{0t}} = 0 \quad (2.10b)$$

$$\frac{\partial(y_t^\rho)}{\partial a_{jt}} + \beta \frac{\partial(E_t \dot{U}_{t+1}^\gamma)^{1/\gamma}}{\partial a_{jt}} = 0 \quad (2.10c)$$

Equation (2.10a) means that the marginal current utility gained from the current consumption ($\frac{\partial(y_t^\rho)}{\partial y_t}$) equals the marginal future utility lost from current consumption

($\frac{\partial(E_t \dot{U}_{t+1}^\gamma)^{1/\gamma}}{\partial y_t}$) times the time discounting factor (β) at optimal consumption level.

Equations (2.10b) and (2.10c) mean that the marginal current utility lost from the current

investment $(\frac{\partial(y_t^\rho)}{\partial a_t})$ equals the marginal future utility gained from the current investment

$(\frac{\partial(E_t \dot{U}_{t+1}^\gamma)^{1/\gamma}}{\partial a_t})$ times the time discounting factor (β) at optimal investment level.

By the definition of \dot{U}_t we have

$$\begin{aligned} \frac{\partial(E_t \dot{U}_{t+1}^\gamma)^{1/\gamma}}{\partial y_t} &= ((E_t \dot{U}_{t+1}^\gamma)^{1/\gamma})^{(1-\gamma)} E_t [\dot{U}_{t+1}^{\gamma-1} \frac{\partial \dot{U}_{t+1}}{\partial y_{t+1}} \frac{\partial y_{t+1}}{\partial A_t} \frac{\partial A_t}{\partial y_t}] \\ &= (E_t \dot{U}_{t+1}^\gamma)^{(\frac{1}{\gamma}-1)} E_t [\dot{U}_{t+1}^{\gamma-1} (\rho y_{t+1}^{\rho-1}) (\frac{\lambda R_{t+1}}{q_{t+1}}) (-q_t)] \end{aligned} \quad (2.11a)$$

$$\begin{aligned} \frac{\partial(E_t \dot{U}_{t+1}^\gamma)^{1/\gamma}}{\partial a_{0t}} &= ((E_t \dot{U}_{t+1}^\gamma)^{1/\gamma})^{(1-\gamma)} E_t [\dot{U}_{t+1}^{\gamma-1} \frac{\partial \dot{U}_{t+1}}{\partial y_{t+1}} \frac{\partial y_{t+1}}{\partial a_{0t}}] \\ &= (E_t \dot{U}_{t+1}^\gamma)^{(\frac{1}{\gamma}-1)} E_t [\dot{U}_{t+1}^{\gamma-1} (\rho y_{t+1}^{\rho-1}) (\frac{1+r_{t+1}}{q_{t+1}})] \end{aligned} \quad (2.11b)$$

$$\begin{aligned} \frac{\partial(E_t \dot{U}_{t+1}^\gamma)^{1/\gamma}}{\partial a_{jt}} &= ((E_t \dot{U}_{t+1}^\gamma)^{1/\gamma})^{(1-\gamma)} E_t [\dot{U}_{t+1}^{\gamma-1} \frac{\partial \dot{U}_{t+1}}{\partial y_{t+1}} \frac{\partial y_{t+1}}{\partial a_{jt}}] \\ &= (E_t \dot{U}_{t+1}^\gamma)^{(\frac{1}{\gamma}-1)} E_t [\dot{U}_{t+1}^{\gamma-1} (\rho y_{t+1}^{\rho-1}) (\frac{\frac{\partial \pi_{t+1}}{\partial a_{jt}} + (p_{j,t+1} + v_{j,t+1})}{q_{t+1}})] \end{aligned} \quad (2.11c)$$

And we have

$$\frac{\partial(y_t^\rho)}{\partial y_t} = \rho y_t^{\rho-1} \quad (2.12a)$$

$$\frac{\partial(y_t^\rho)}{\partial a_{0t}} = \rho y_t^{\rho-1} \frac{\partial y_t}{\partial a_{0t}} = \rho y_t^{\rho-1} (\frac{1}{-q_t}) \quad (2.12b)$$

$$\frac{\partial(y_t^\rho)}{\partial a_{jt}} = \rho y_t^{\rho-1} \frac{\partial y_t}{\partial a_{jt}} = \rho y_t^{\rho-1} (\frac{p_{j,t} + v_{j,t}}{-q_t}) \quad (2.12c)$$

Substitute equations (2.11) and (2.12) into equation (2.10), we have

$$\beta (E_t \dot{U}_{t+1}^\gamma)^{(\frac{1}{\gamma}-1)} E_t [\dot{U}_{t+1}^{\gamma-1} (y_t/y_{t+1})^{1-\rho} (q_t/q_{t+1}) \lambda R_{t+1}] = 1 \quad (2.13a)$$

$$\beta (E_t \dot{U}_{t+1}^\gamma)^{(\frac{1}{\gamma}-1)} E_t [\dot{U}_{t+1}^{\gamma-1} (y_t/y_{t+1})^{1-\rho} (q_t/q_{t+1}) (1 + r_{t+1})] = 1 \quad (2.13b)$$

$$\beta(E_t \dot{U}_{t+1}^\gamma)^{\left(\frac{1}{\gamma}-1\right)} E_t[\dot{U}_{t+1}^{\gamma-1}(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\left(\frac{\partial \pi_{t+1}}{\partial a_{j,t}} + (p_{j,t+1} + v_{j,t+1})\right)] = (p_{j,t} + v_{j,t}) \quad (2.13c)$$

Now we define a new discounting factor β' , which includes four elements:

$\beta' = \beta d_1 d_2 d_3$, where

$$d_1 = \frac{(E_t \dot{U}_{t+1}^\gamma)^{\left(\frac{1}{\gamma}-1\right)}}{E_t[\dot{U}_{t+1}^{\gamma\left(\frac{1}{\gamma}-1\right)}]} \quad (2.14a)$$

$$d_2 = E_t[\dot{U}_{t+1}^{\gamma-1}] E_t[\dot{U}_{t+1}^{1-\gamma}] \quad (2.14b)$$

$$d_3 = \frac{E_t[\dot{U}_{t+1}^{\gamma-1}(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}]}{E_t[\dot{U}_{t+1}^{\gamma-1}] E_t[(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}]} \quad (2.14c)$$

We rewrite the first order conditions with respect to y_t , a_{0t} , and a_{jt} as

$$\beta' E_t[(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}] = 1 \quad (2.15a)$$

$$\beta' E_t[(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})(1 + r_{t+1})] = 1 \quad (2.15b)$$

$$\beta' E_t[(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\left(\frac{\partial \pi_{t+1}}{\partial a_{j,t}} + (p_{j,t+1} + v_{j,t+1})\right)] = (p_{j,t} + v_{j,t}) \quad (2.15c)$$

where $\frac{\partial \pi_{t+1}}{\partial a_{j,t}} = \zeta \frac{\pi_{t+1}}{a_{j,t}}$

Here we model the profit function π_{t+1} with homogeneity, which is a simplification. In fact, the profit function could be heterogeneous in land acreage.

Equation (2.15a), (2.15b), and (2.15c) are used as a system for parameter estimation and out-of- sample prediction for the rest of the paper. Several special cases are discussed in Appendix C, including the familiar time additive utility (Lucas 1978; Weil 1989, 1990; Bank and Riedel 2000).

Now we discuss the terms in the context of land valuation. Similar to equation (2.15a) and (2.15b), (2.15c) means that the marginal utility lost from the current investment in farmland assets, measured in $((p_{j,t} + v_{j,t}))$, equals the marginal utility gained from the future returns in those farmland assets, measured in $(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})(\frac{\partial \pi_{t+1}}{\partial a_{j,t}} + (p_{j,t+1} + v_{j,t+1}))$, times the general discounting factor (β') at optimal investment level.

2.3. Data and Estimation

In this section, we discuss the data collected for estimation of equation (2.15), and illustrate the estimation method used for the DLPM estimable form derived in Section II. The above model is developed for a representative agent and we assume that all the functional forms can be applied to aggregated data.

2.3.1. Data

The data are collected from the USDA website, <http://www.ers.usda.gov/data-products/farm-income-and-wealth-statistics.aspx>. They are annual time series data for the period of 1950~2008 at the US national level. The gross rate of return on farm equity is calculated as a ratio of gross return to farming to farm wealth levels. The farm wealth levels are collected from the balance sheet. Table 2.1 shows the descriptive statistics of the data. Parameters are defined in table 2.2.

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

Table 2.1. Descriptive Statistics, 1950-2010

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 61

Table 2.2. Parameter Definitions

Parameter	Definition	Economic Implication
ρ	$\sigma = 1/(1 - \rho)$	σ is the intertemporal elasticity of substitution
γ	$\gamma \equiv \alpha/\rho$	γ is the ratio of α to ρ
β'	$\gamma = 2 - \beta'(\bar{r} + 1)$	β' is a general discounting factor
c_m	$v_t = c_m \Delta Q_t$ if $\Delta Q_t < 0$	c_m is diminishing market transaction cost coefficient
c_p	$v_t = c_p \Delta Q_t$ if $\Delta Q_t > 0$	c_p is booming market transaction cost coefficient
α	$M_t = (E_t U_{t+1}^\alpha)^{\frac{1}{\alpha}}$	the relative risk aversion coefficient is a decreasing function of α .
λ	$G_t = A_{t-1}^\lambda K_t$	λ is homogeneity degree of return function
ζ	$\frac{\partial \pi_{t+1}}{\partial a_{j,t}} = \zeta \frac{\pi_{t+1}}{a_{j,t}}$	ζ is homogeneity degree of profit function

- 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 (\$1,000/acre)
- π_{t+1} / a_{kt} : net farm income per acre (\$1000/acre)
- v_t : transaction costs of year t in farmland market (\$1,000/acre),

where $v_t = c_p \Delta Q_t$ if $\Delta Q_t > 0$, and $v_t = c_m \Delta Q_t$ if $\Delta Q_t < 0$,

where $\Delta Q_t = Q_t - Q_{t-1}$, Q_t is the land quantity at time t,

where c_m and c_p are coefficients

2.3.2. Estimation Method: Two-stage GMM

The system of equation (2.15) is estimated as a general homogeneous model. We will also estimate a variant where we set homogeneity degree to 1, a linear homogeneous model, which is identical to that in Chavas and Thomas 1999. Since both models are highly nonlinear, we take a typical approach, two-stage GMM, to estimate parameters.

GMM has possibly been most frequently applied in empirical finance (Hall 2005). Hansen (1982) introduced GMM with its fundamental statistical theory, while Hansen and Singleton (1982) revealed the potential of the GMM approach to estimation through their empirical analyses of asset pricing. When the distribution of the data is not assumed correctly, maximum likelihood estimation (ML) is not optimal and the resulting

estimator may even be inconsistent (Hansen and Singleton 1982). But GMM estimation is based on population moment conditions, and therefore GMM can be preferred to ML in nonlinear Euler equation models (Hansen and Singleton 1982).

Hansen (1992) showed that an asymptotically efficient or optimal GMM estimator 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 weight matrix, which is a heteroskedasticity and autocorrelation consistent estimator of the long-run covariance matrix based on an initial estimate of the parameter vector. To do this we first we calculate the initial parameter estimates of the nonlinear system with two-stage least squares (2SLS) estimation by iterated convergence. Second, we use the 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, $\left(\frac{1}{T} \sum_{t=1}^T g(Y_t, \theta)\right)' \hat{W} \left(\frac{1}{T} \sum_{t=1}^T g(Y_t, \theta)\right)$, obtained in stage one with respect to parameter vector. The non-linear optimization for the parameter vector iterates to convergence of 0.0001, updating parameter estimates from the initial 2SLS estimation to the final two-stage GMM. Further, for the HAC procedure, we specify that the data is processed with pre-whitening by VAR(1) and we choose the Bartlett kernel and Newey-West bandwidth (Beyer et al 2008). Under suitable conditions GMM estimator is consistent, asymptotically normal, and with right choice of weighting matrix W asymptotically efficient.

2.3.3. Error Correction

Two-stage GMM is known for its undersized error terms. Monte Carlo studies have shown that estimated asymptotic standard errors of the efficient two-staged GMM estimator can be severely downward biased in small samples (Windmeijer 2005). In order to enhance the validity of hypothesis tests, the variances of the two-stage GMM estimation are corrected through the Taylor Expansion according to Windmeijer (2005). The calculation is executed in MATLAB with Windmeijer's variance formula for general models.

2.4. Estimation Results

2.4.1. Estimation

Table 2.3 reports the Two-stage GMM estimation for the general homogeneity model under error correction. Table 2.4 compares the estimation results between the linear and the general homogeneity model.

Table 2.3 reports the estimated coefficients with their standard errors from the two-stage GMM, together with the corrected standard errors and ratios of correction. To evaluate the correction of the downward bias of standard errors, we calculate the ratio of correction as the ratio between the corrected standard errors and the original two-stage GMM standard errors. Table 2.4 shows that the ratio of correction ranges from 2.5 to 10.7, indicating that the correction was needed.

Table 2.3. Two-Stage GMM Estimation Results of General Homogeneity Model with Corrections, 1950-2010

	Estimate	Std. Error	Corrected Std. Error	Ratio of Correction
ρ	0.9904	0.0026	0.0276	10.7353
γ	0.9602	0.0004	0.0014	3.8491
β'	0.9882	0.0003	0.0013	3.8491
c_m	-0.0158	0.0013	0.0065	5.0512
c_p	0.1442	0.0285	0.0720	2.5227
α	0.9510	0.0025	0.0265	10.6356
λ	0.8982	0.0007	0.0039	5.7522
ζ	0.6025	0.0493	0.1868	3.7856

Note: the General Homogeneity parameters are estimated from equations (2.15a), (2.15b), and (2.15c) with Two-stage GMM procedure, in Eviews7.

The error corrections are performed according to Windmeijer 2005, in MATLAB.

Table 2.4. GMM Estimation Results for Linear Homogeneity and General Homogeneity Model, 1950-2010

	Linear Homogeneity		General Homogeneity	
	Estimate	Std. Error	Estimate	Std. Error
P	0.7547**	0.0807	0.9904**	0.0276
γ	0.9701**	0.1115	0.9602**	0.0014
β'	0.9726**	0.1279	0.9882**	0.0013
c_m	0.0084	0.0145	-0.0158*	0.0065
c_p	0.2062	0.2318	0.1442*	0.0720
α	0.7321**	0.1323	0.9510**	0.0265
λ	1.0000	-	0.8982**	0.0004
ζ	1.0000	-	0.6025**	0.1868
J-stat	0.1085		2.2128	
R^2 equation (a)	0.5174			
R^2 equation (b)	0.2345			
R^2 equation (c)	-			

Note: * and ** denote a parameter significantly different from zero at the 5% and 1% levels, respectively.

The Linear Homogeneity parameters are estimated from Chavas and Thomas 1999, while the General Homogeneity parameters are estimated from equations (2.15a), (2.15b), and (2.15c).

In statistics, the coefficient of determination, denoted R^2 , is used in the context of statistical models whose main purpose is the prediction of future outcomes on the basis of other related information. R^2 is most often seen as a number between 0 and 1.0, used to describe how well a regression line fits a set of data.

The linear homogeneity model estimates are almost identical to those of Chavas and Thomas. Now we discuss the main differences between the results from linear homogeneity model and general homogeneity model.

The general homogeneity model yields a much higher estimate for ρ , and therefore much higher intertemporal elasticity of substitution, $\sigma=1/(1-\rho)$. In particular the linear model elasticity of substitution is 4.0650 while the general homogeneity model estimate is 104.1667. This indicates that it is much easier for agents in the US farmland market to substitute their current consumption for future consumption than the linear model shows. In other words, the agents in the US farmland markets have higher flexibility to postpone their consumption or higher tendency to hold onto their farmland investments than traditional dynamic farmland pricing models predict.

The linear homogeneity model estimate for ρ is 0.754, and the corresponding intertemporal elasticity of substitution is 4.0650, very close to 4.13, the estimate of that in Chavas and Thomas (1999). As defined in table 2.2, ρ does not have any independent economic definition, but is deemed as a reflector of σ , intertemporal elasticity of substitution. However, the general homogeneity model estimate for ρ is 0.9904 and the corresponding intertemporal elasticity of substitution is 104.1667. This result indicates that the curvature of the utility indifference curve, or, the substitutability between consumptions of this period and next period, y_t and y_{t+1} , is much higher than the linear homogeneity model estimates.

Table 2.5. Hypothesis Testing, 1950-2010

		Linear Homogeneity		General Homogeneity	
		Test Statistic	p-Value	Test Statistic	p-Value
Overidentifying restrictions	(Hansen test)	$\chi^2(5) = 0.1085$	0.9998	$\chi^2(18) = 2.2128$	0.9999
No transaction costs	$(c_p = c_m = 0)$	$\chi^2(2) = 1.0923$	0.5792	$\chi^2(2) =$	0.0000
Symmetric transaction costs	$(c_p = c_m)$	$\chi^2(1) = 0.7284$	0.3934	$\chi^2(1) =$	0.0000
Expected utility	$(\gamma = 1)$	$\chi^2(1) = 0.0718$	0.7887	$\chi^2(1) = 806.3214$	0.0000
Infinite intertemporal elasticity of substitution	$(\rho = 1)$	$\chi^2(1) = 8.1808$	0.0042	$\chi^2(1) = 0.1204$	0.7286
0 rate of time preference	$(\beta = 1)$	$\chi^2(1) = 0.0007$	0.9790	$\chi^2(1) = 78.3039$	0.0000
Risk neutrality	$(\alpha = 1)$	$\chi^2(1) = 3.6801$	0.0551	$\chi^2(1) = 3.4161$	0.0646
Linear Homogeneity	$(\lambda = 1)$	$\chi^2(1) = -$		$\chi^2(1) = 674.8322$	0.0000
Linear Homogeneity	$(\zeta = 1)$	$\chi^2(1) = -$		$\chi^2(1) = 4.5279$	0.0333

Note: The Linear Homogeneity parameters are estimated from Chavas and Thomas 1999, while the General Homogeneity parameters are estimated from equations (2.15a), (2.15b), and (2.15c).

This finding is highly supported by anecdotal reports on farmers' reluctance to sell their land. For instance, Iowa Land Value Survey shows that less than 2% of the farmland in Iowa is sold each year, and 74% of it ends up in the hands of local farmers, who tend to buy for the long term (Professional Farmers of America, Inc. 2011). Agricultural Credit Conditions Surveys conducted by Federal Reserve Bank of Kansas City also indicate farmers' reluctance to sell land even when farmland values are near record high (Henderson and Akers 2012).

Intuitively, high intertemporal elasticity of substitution helps to explain boom and bust cycles. It is commonly observed that farmland values go through long booms and short busts. Farmland prices boom when economic indicators suggest an unsustainable boom, perhaps because of farmers' tendency to hold on their farmland investments. High intertemporal elasticity of substitution means that farmers are very flexible in postponing their consumption, and probably hold onto their investments, which explains the extended boom period or the delayed bust start.

A second point showed in tables 2.4 and 2.5 is that the general homogeneity model yields statistically significant estimates of transaction cost coefficients, C_p and C_m . In the linear homogeneity model, both transaction cost parameters are insignificant. In the general homogeneity model, the estimate of booming market transaction cost coefficient, C_p , is 0.1442 with standard error of 0.0720, positive and significant at 5% level. The estimate of the diminishing market transaction cost coefficient, C_m , is negative and significant at 5% level. These results indicate that transaction costs, $v_{jt}(m_{jt})$,

remain positive regardless of the direction of farmland quantity changes. This finding differs from that of the linear homogeneity model with both positive C_m and C_p .

Now we look at the estimation from general homogeneous model. When the farmland quantity is increasing, the transaction costs equal booming market transaction cost coefficient (C_p) times farmland quantity change, $v_{jt}(m_{jt}) = v_j^+ = c_p \Delta Q_t$. Since both the coefficient and change are positive, the transaction costs will be positive. When the farmland quantity is decreasing, the transaction costs equal diminishing market transaction cost coefficient (C_m) times farmland quantity change, $v_{jt}(m_{jt}) = v_j^- = c_m \Delta Q_t$. Since both the coefficient and change are negative, the transaction costs will still be positive. This is consistent with the observation that selling land costs money whatever the market form.

The opposite signs of the transaction cost parameters in booming and diminishing markets are consistent with real world observations. In the US farmland market, both the buyers and sellers of farmland need to pay positive transaction costs, such as advertisements, research, legal fees, and so on in order to close the transaction. Therefore, it is reasonable to expect positive aggregated transaction costs in both booming and diminishing markets.

The magnitude difference between two coefficients is sensible because when the market is diminishing, agents become more cautious and this leads to an increase in market efficiency. In a diminishing market, the transaction amount decreases, and only the most economically efficient deals are closed in the market, for instance, brokers may

give discounts to get people to sell, which yields a much lower transaction cost coefficient.

A third finding is that the general homogeneity model yields a much higher estimate for α , and therefore much lower risk aversion. We follow Epstein and Zin (1991)'s definition of the risk aversion coefficient: agents are risk neutral when their $\alpha = 1$, and they become more risk averse when α decreases. In the linear homogeneity model, the estimate of α is 0.7321 with standard error of 0.1323, positive and significant at 1% level. In the general homogeneity model, the estimate of α is 0.9510 with standard error of 0.0265, positive and again significant. These results indicate that the agents in US farmland market are much less risk averse than has been found under the traditional CAPM model estimates (Chavas and Thomas 1999).

The finding of lower risk aversion helps explain the equity premium puzzle in the farm sector (Mehra and Prescott 1985). It has been well documented that the farm sector has a lower return rate than the capitalization formula suggested in the capital (Moss and Katchova 2005). Our results show that the low return rate in farm sector could be explained by the low risk aversion of farmers.

Finally we find that the estimate of λ , the homogeneity degree of the gross return function, is less than 1, and therefore we find a concave return function. The general homogeneity model estimate for λ is 0.8982, with standard error of 0.0004, positive and significant at 1% level. This result means that the gross rate of return, $R_t = A_{t-1}^{\lambda-1} K_t$, is a decreasing function of asset level, A_{t-1} , since $\lambda < 1$.

It is straight forward that efficiency always goes in the opposite direction of scale in a concave return economy. In a booming stage, the scale of the investment continues to increase, and the return rate continues to decrease. This booming stage will continue without slowing down or fading into a static stage, because once the expected utility elasticity of investment ($\omega = \frac{\partial M_t / \partial A_t}{M_t / A_t}$) goes beyond the upper bound of the stability range; it will increase in an accelerating manner and form a bubble.

In the economics literature, a bubble is defined as "trade in high volumes at prices that are considerably at variance with intrinsic values" (Lahart 2008; Shiller 2012), or, a trade in products or assets with inflated values. Many explanations have been suggested for the formation of a bubble, but recent researches show that bubbles appear even without uncertainty (Smith, Suchanek, and Williams 1988; Smith et al 1993), speculation (Lei, Noussair, and Plott 2001), or bounded rationality (Levine and Zajac 2007). Our model provides a new explanation of the form of farmland price bubble under the concave return function.

Bubbles are often identified in retrospect when a sudden drop in prices appears. Such a drop is known as a crash or a bubble burst. Our model shows that the booming stage will continue till the return rate decreases to such a low level that further increase in investment becomes unsustainable. This unsustainability is reflected in instability and in Appendix D a proof appears of instability under concave return function. Under this instability the asset value will drop sharply, the asset level will decrease, and a bust stage starts. In other words, our model suggests that a bust is inevitable for a bubble in farmland prices.

In short, a concave return economy illustrates embedded instability in dynamic CAPM models by explaining the forming of a bubble during a boom. The reverting mechanism between scale and efficiency explains the inevitability of a bust after the boom. Together, the general homogeneity model helps to explain the boom-bust cycles in farmland values.

A concave return function is observed likely because of diverse land quality. Namely doubling the land use in the farm sector does not double the return to agriculture because of the varied productivity of land and the fact that expansion causes one to move onto lower productivity lands. By the nature of farm business, farmers would always first plant on the more productive land and turn to less productive land later. This is manifest in our model in the form of decreasing marginal net farm income per acre. The degree of homogeneity of the net farm income, ζ , is estimated to be 0.6025, significantly less than 1. Therefore, the marginal net farm income is a decreasing function of farmland acreage, which reflects the nonlinear relationship embedded in land quality.

Other studies have shown this nonlinearity in the case of land use contractions. For example, when the farm acreage set-aside program caused retirement of land, the productivity was found to fall by a lesser percentage (Wu, Ziberman and Babcock 2001).

2.4.2. Predictions

Now, we compare the predictions from both linear and general homogeneity models with actual data. One-year-ahead predictions from both the general model and linear model were made for year 2000-2010 using a rolling process. The forecasts are

generated in a rolling process with fixed start year of 1950. For instance, the forecasted land price in 2000 is calculated with coefficients estimated with data in 1950~1999, the forecasted land price in 2001 is calculated with coefficients estimated with data in 1950~2000, and so on. We actually use period t exogenous variables in forecasting land values for period t . Therefore, our work is not truly “out of sample”.

Analysis in Tetrad 4 shows that the general model predictions D-separate (Bessler and Akleman 1998) the linear model predictions from the actual data. Figure 2.1 demonstrates this relationship in a directed acyclic graph (DAG) from a greedy equivalent search (GES) (Chickering 2002). Figure 2.2 illustrates the predicted land prices generated for year 2000-2010. The Root Mean Squared Errors (RMSE) for linear and general homogeneity model predictions are calculated as 0.1315 and 0.0979 respectively. Both figures provide evidences that general homogenous model generates better out-of-sample predictions than linear homogeneous model.

2.5. Conclusion

In this chapter, we find that altered assumptions in the traditional CAPM of linear return functions help identify the causes of boom-bust cycles in farmland valuations. Specifically, concavity of return functions illustrates the embedded instability of optimizations of dynamic CAPM. It is mathematically proved that the concavity of return functions regulates that the dynamic CAPM optimization grows in an exponential manner over time. Concave returns to asset investments in the farm sector mean that the gross return rate of farmland assets decreases as the asset level increases. The

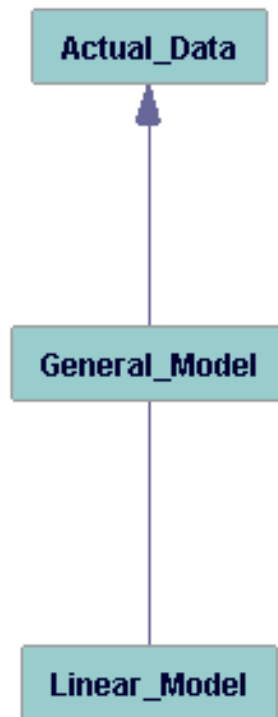


Figure 2.1. DAG of Data and Predictions

Note: Tetrad 4 shows that the general model predictions D-separate the Linear model predictions from the actual data.

The relationship is searched in GES, a Bayesian search algorithm, greedy equivalent search.

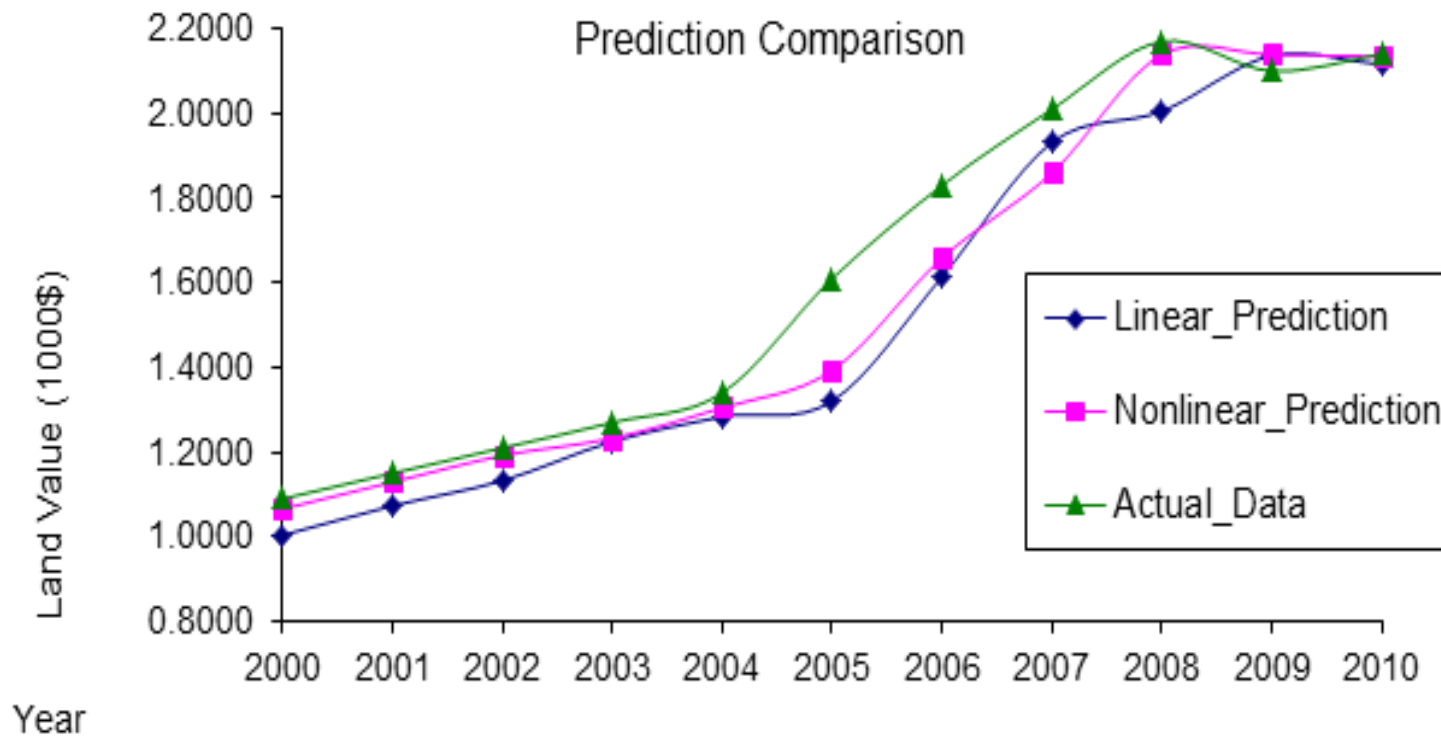


Figure 2.2. Prediction Comparison for Linear Homogeneity Model and General Homogeneity Model

Note: One-year-ahead predictions from both the general model and linear model were made for year 2000-2010 using a rolling process. The Root Mean Squared Errors (RMSE) for linear and general homogeneity model predictions are 0.1315 and 0.0979 respectively.

growth of dynamic CAPM solutions indicates a bubble, and thus a boom-bust cycle, in farmland valuation. In other words, this essay explained the short-term boom-bust cycles in farmland valuations with the concave character of asset returns in farmland.

We also find that intertemporal elasticity of substitution, risk aversion, and transaction costs are important determinants for farmland valuations. First, farmers' willingness to delay consumption, as found through their high intertemporal elasticity of substitution, indicates that farmers are likely to hold on to land through bust cycles, which raises the value of land and shortens the bust. High intertemporal elasticity of substitution also means that farmers are likely to forgo immense consumption and instead acquire additional land during a boom cycle, which inflates land values and prolongs the boom. Second, we find much lower risk aversion in the agents on farmland market than previous studies, indicating that farmers will not accept low farmland prices to avoid the risks in farm business. This rigidity of farmland prices related to low risk aversion also helps to explain the prolonged boom stages and inevitability of bust stages in farmland valuation. Third, we find, as others have found (Chavas and Thomas 1999), that transaction costs vary across different stages of farmland valuation cycles. We argue that these costs do not give rise to the cycles.

In short, our explanation of the boom-bust cycles in farmland valuation is rooted in the homogeneity of return functions. We find concavity (homogeneity less than 1) in farmland asset returns, which is consistent with the decreasing marginal returns to additional farmland assets. This essay provides empirical evidence for the connection between concavity of asset returns and boom-bust cycles in farmland valuations.

This chapter has made several important methodological contributions. In particular, estimating CAPM in a framework that permits nonlinear homogenous returns provides scholars a platform to explore the imbedded dynamic instability of CAPM. We also find that the non-linear homogeneous model generates better out-of-sample predictions than the linear homogeneity model, proposing a powerful alternative model in the literature of farmland valuation.

CHAPTER III

THE VALUE OF ECONOMIC INFORMATION IN PREDICTIONS OF FARMLAND PRICES

The Dynamic Land Pricing Model (DLPM) as developed in Chapter II can be used to generate forecasts of land prices. Errors from these forecasts involve both backward information and forward information. This chapter addresses the apparent overpricing of farmland values by decomposing the variance of forecast errors in the CAPM (forward) portion and the Random Walk (backward) portion. The estimation errors from Random Walk of exogenous (explanatory) variables are considered backward, because only historical data are used and no economic information is adopted in the estimation. The error terms from CAPM are considered forward, because CAPM uses the economic information on the relationship among different variables to estimate the future values of endogenous (dependent) variables.

3.1. Background

Even with the assumption of perfect and costless markets, individuals face risks of returns attainable from their own productive investments imposed by technological uncertainty (Hirshleifer 1971). Information is used to reduce risks in the decision process for economic agents, and the value of information could be measured by the expected utilities with different information sets. Besides the value of economic information, the distributive aspect of access to information is also an important issue in the literature. In

the land valuation context, information is the relationship between farmland prices and other variables specified in the CAPM.

The objective of this essay is to explain the apparent overpricing of farmland with the analysis of the value of economic information through forecast error variance decomposition (FEVD) of QRE between CAPM and RW error terms. This essay presents an analysis of the value of economic information in the land valuation context. The DLPM framework with concave return functions developed in Chapter II is adopted to generate QRE predictions, and the variance of the predictions is decomposed into the CAPM (forward) part and RW (backward) part. This study identifies structural changes in farmland prices over the period of 1970-2010, and then defines different stages according to those break points. The portions of the CAPM part at different stages are compared to study the value of economic information in different scenarios of farmland pricing.

3.1.1. Quasi-Rational Expectations

After Muth (1961) introduced the rational expectations (RE) hypothesis, Nerlove (1967, 1971, and 1972) proposed a variant called Quasi-Rational Expectation or QRE, which was discussed in detail by Nerlove, Grether, and Carvalho (1979). RE assumes that economic agents make purposeful and efficient use of information in optimizing their decisions. QRE is a form of rational expectations obtained by neglecting some of the restrictions implied by the RE hypothesis.

Nerlove and Bessler (2001) proposed several reasons why RE may fail in a realistic market. First, the objective functions for optimization may not satisfy the quadratic assumption under linear stochastic constraints. Second, “agents are learning about both the processes generating exogenous variables and/or about the model characterizing their behavior in aggregate” (Horvath and Nerlove 1996). For example, Tellis and Gaeth (1990) found that consumers select different choice strategies, rational, overweighting, and underweighting, when information on product quality is not perfect. Third, the empirical model may suffer from misspecifications in behavior, dynamics, and information measurements (Pesaran 1987).

We adopt the DLPM developed in Chapter II to estimate and predict future land prices, which is consistent with the basic tenet of RE hypothesis. However, in order to make a more realistic analysis of farmland prices, we adopt QRE instead of RE, and assume that the agent does NOT have all the exogenous information needed in the DLPM to predict future land prices. We assume that the agent needs to use historical data on those exogenous variables to generate a naïve estimate as the necessary exogenous information for DLPM. Therefore, we have two kinds of errors in our model. First, when the agent uses historical data to make a naïve estimate of exogenous variables needed in DLPM, there are differences between those estimates and later realized data. We treat this kind of differences as backward errors, since the estimation is based on historical data and no economic theory is used. Second, when the agent uses DLPM to predict future land prices, there will be errors in the estimation and prediction of DLPM and we treat those errors as forward errors. The forward error terms present

the shocks in the DLPM and allow us to evaluate the economic information in the model.

3.1.2. The Value of Economic Information

The economic theory of information value has progressed considerably over the years (Katz and Murphy 1997; Letson, Sutter, and Lazo 2007). The von Neumann-Morgenstern utility hypothesis and the decision theory under uncertainty (Arrow 1965; Pratt 1964) accelerated the development of value-of-information theory. The adoption of stochastic distribution models provides new means to measure the value of information in recent years (Athey and Levin 1998).

Modern economic theory deems information as a factor in the decision process for economic agents to reduce risks, and that such information will be of value to decision makers (Morris and Shin 2002). Some individual decision models use subjective probabilities and utility rankings for all possible outcomes to capture information (Von Neumann and Morgenstern 1953; Winkler 1972). In those models, the value of information for individuals can be measured as the difference between expected utilities with and without the information set (Hilton 1981; Gregory Mankiw and Shapiro 1986). For instance, Levitt and Syverson (2008) found that real estate agents are often better informed than their clients, and this information advantage is related to a 3.7% premium in the house prices received for those agents.

Chavas and Johnson (1983) and Pesaran (1987) pointed out that there are interesting parallels between the value-of-information theory and the rational expectation

hypothesis. The rational expectation hypothesis provides a framework to investigate the market valuation of information.

3.1.3. Forecast Error Variance Decomposition

As we know, forecast error variance decomposition has been widely used in linear models, and the variance decomposition in Vector Auto Regression (VAR) models is a powerful tool to study the causality structure in data. In this chapter, we adopt the forecast error variance decomposition procedure to study the value of economic information in farmland prices.

This study analyzes the value of economic information carried in CAPM through forecast error variance decomposition (FEVD). In other words, we are able to show the proportion of uncertainty at different horizons into the future. The portions are accounted for by values of exogenous variables (backwards) and endogenous variables (forward) as defined in the CAPM model. This demonstration allows analysts to better understand the relative contribution of each CAPM component.

The remainder of the essay is organized as following: Section II describes the model. Section III describes the data, the estimation and structure change. Section IV illustrates the decomposition of the forecast error variance. Section V summarizes and concludes the essay.

3.2. The Model

This chapter uses the dynamic land pricing model (DLPM) developed in Chapter 2 to generate predictions. Our analysis continues with equation (2.15), the first order conditions generated for parameter estimation and out-of-sample prediction in Chapter 2. All existing variables are defined as in Chapter 2.

$$\beta' E_t \left[\left(\frac{y_t}{y_{t+1}} \right)^{1-\rho} \left(\frac{q_t}{q_{t+1}} \right) \lambda R_{t+1} \right] = 1 \quad (3.1a)$$

$$\beta' E_t \left[\left(\frac{y_t}{y_{t+1}} \right)^{1-\rho} \left(\frac{q_t}{q_{t+1}} \right) (r_{t+1} + 1) \right] = 1 \quad (3.1b)$$

$$\beta' E_t \left[\left(\frac{y_t}{y_{t+1}} \right)^{1-\rho} \left(\frac{q_t}{q_{t+1}} \right) \left(\frac{\partial \pi_{t+1}}{\partial a_t} + (p_{t+1} + v_{t+1}) \right) \right] = (p_t + v_t) \quad (3.1c)$$

$$\text{where } \frac{\partial \pi_{t+1}}{\partial a_t} = \zeta \frac{\pi_{t+1}}{a_t}$$

First, we rearrange all three conditions

$$\Rightarrow U_{0,t+1} = 1 - \beta' \left(\frac{y_t}{y_{t+1}} \right)^{1-\rho} \left(\frac{q_t}{q_{t+1}} \right) \lambda R_{t+1} \quad (3.2a)$$

$$\Rightarrow U_{1,t+1} = 1 - \beta' \left(\frac{y_t}{y_{t+1}} \right)^{1-\rho} \left(\frac{q_t}{q_{t+1}} \right) (r_{t+1} + 1) \quad (3.2b)$$

$$\Rightarrow U_{2,t+1} = (p_t + v_t) - \beta' \left(\frac{y_t}{y_{t+1}} \right)^{1-\rho} \left(\frac{q_t}{q_{t+1}} \right) \left(\zeta \frac{\pi_{t+1}}{a_t} + (p_{t+1} + v_{t+1}) \right) \quad (3.2c)$$

To study the land price, we further rearrange the third condition (3.2c)

$$\Rightarrow p_{t+1} = [(p_t + v_t) - U_{2,t+1}] / \left[\beta' \left(\frac{y_t}{y_{t+1}} \right)^{1-\rho} \left(\frac{q_t}{q_{t+1}} \right) \right] - \left(\zeta \frac{\pi_{t+1}}{a_t} + v_{t+1} \right) \quad (3.3)$$

$$\Rightarrow (p_{t+1} + v_{t+1}) = [(p_t + v_t) - U_{2,t+1}] / \left[\beta' \left(\frac{y_t}{y_{t+1}} \right)^{1-\rho} \left(\frac{q_t}{q_{t+1}} \right) \right] - \left(\zeta \frac{\pi_{t+1}}{a_t} \right) \quad (3.4)$$

To simplify notation, we define

$$Y_{t+1} \equiv (p_{t+1} + v_{t+1}), Z_{t+1} \equiv \frac{1}{\beta'} \left(\frac{y_{t+1}}{y_t} \right)^{1-\rho} \left(\frac{q_{t+1}}{q_t} \right), \text{ and } X_{t+1} \equiv -\frac{\pi_{t+1}}{a_t}$$

$$\Rightarrow Y_{t+1} = Z_{t+1}Y_t + \zeta X_{t+1} - U_{2,t+1}Z_{t+1} \quad (3.5)$$

In order to generate QRE predictions of land prices, we treat X_{t+1} , Z_{t+1} , and v_{t+1} as random walk variables with drifts:

$$X_{t+1} = a_1 + b_1X_t + \epsilon_{1,t+1} \quad (3.6)$$

$$Z_{t+1} = a_3 + b_3Z_t + \epsilon_{3,t+1} \quad (3.7)$$

$$v_{t+1} = a_4 + b_4v_t + \epsilon_{4,t+1} \quad (3.8)$$

Substitute X_{t+1} and Z_{t+1} into Y_{t+1}

$$\begin{aligned} \Rightarrow Y_{t+1} &= (a_3 + b_3Z_t + \epsilon_{3,t+1})Y_t + \zeta(a_1 + b_1X_t + \epsilon_{1,t+1}) - U_{2,t+1}Z_{t+1} \\ &= \zeta b_1X_t + a_3Y_t + b_3Z_tY_t + \zeta a_1 + \zeta \epsilon_{1,t+1} + Y_t \epsilon_{3,t+1} - U_{2,t+1}Z_{t+1} \end{aligned} \quad (3.9)$$

Assume error terms are iid

$$\epsilon_{1,t+1} \sim N(0, \sigma_1^2), \epsilon_{1,t+1}, \epsilon_{1,t+2}, \epsilon_{1,t+3} \text{ iid} \quad (3.10a)$$

$$U_{2,t+1} \sim N(0, \sigma_2^2), U_{2,t+1}, U_{2,t+2}, U_{2,t+3} \text{ iid} \quad (3.10b)$$

$$\epsilon_{3,t+1} \sim N(0, \sigma_3^2), \epsilon_{3,t+1}, \epsilon_{3,t+2}, \epsilon_{3,t+3} \text{ iid} \quad (3.10c)$$

$$\epsilon_{4,t+1} \sim N(0, \sigma_4^2), \epsilon_{4,t+1}, \epsilon_{4,t+2}, \epsilon_{4,t+3} \text{ iid} \quad (3.10d)$$

Define $\epsilon_{2,t+1} \equiv \zeta \epsilon_{1,t+1} + Y_t \epsilon_{3,t+1} - U_{2,t+1}Z_{t+1}$

$$\begin{aligned} &= \zeta \epsilon_{1,t+1} + Y_t \epsilon_{3,t+1} - U_{2,t+1}(a_3 + b_3Z_t + \epsilon_{3,t+1}) \\ &= \zeta \epsilon_{1,t+1} + Y_t \epsilon_{3,t+1} - U_{2,t+1}a_3 - U_{2,t+1}b_3Z_t - U_{2,t+1}\epsilon_{3,t+1} \end{aligned} \quad (3.11)$$

Substitute $\epsilon_{2,t+1}$ into Y_{t+1}

$$\Rightarrow Y_{t+1} = \zeta b_1X_t + a_3Y_t + b_3Z_tY_t + \zeta a_1 + \epsilon_{2,t+1} \quad (3.12)$$

Rewrite predictions of X_{t+1} , Y_{t+1} , and Z_{t+1} into matrix form

$$\begin{aligned}
\Rightarrow \begin{bmatrix} X_{t+1} \\ Y_{t+1} \\ Z_{t+1} \end{bmatrix} &= \begin{bmatrix} b_1 & 0 & 0 \\ \zeta b_1 & a_3 + b_3 Z_t & 0 \\ 0 & 0 & b_3 \end{bmatrix} \begin{bmatrix} X_t \\ Y_t \\ Z_t \end{bmatrix} + \begin{bmatrix} a_1 \\ \zeta a_1 \\ a_3 \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t+1} \\ \epsilon_{2,t+1} \\ \epsilon_{3,t+1} \end{bmatrix} \\
&= \begin{bmatrix} b_1 & 0 & 0 \\ \zeta b_1 & a_3 & b_3 Y_t \\ 0 & 0 & b_3 \end{bmatrix} \begin{bmatrix} X_t \\ Y_t \\ Z_t \end{bmatrix} + \begin{bmatrix} a_1 \\ \zeta a_1 \\ a_3 \end{bmatrix} + \begin{bmatrix} \epsilon_{1,t+1} \\ \epsilon_{2,t+1} \\ \epsilon_{3,t+1} \end{bmatrix} \tag{3.13}
\end{aligned}$$

$$\Rightarrow d \begin{bmatrix} X_{t+1} \\ Y_{t+1} \\ Z_{t+1} \end{bmatrix} = \begin{bmatrix} b_1 & 0 & 0 \\ \zeta b_1 & a_3 + b_3 Z_t & b_3 Y_t \\ 0 & 0 & b_3 \end{bmatrix} d \begin{bmatrix} X_t \\ Y_t \\ Z_t \end{bmatrix} + d \begin{bmatrix} \epsilon_{1,t+1} \\ \epsilon_{2,t+1} \\ \epsilon_{3,t+1} \end{bmatrix} \tag{3.14}$$

The above derivative matrix form is the structure used in the later analysis of forecast errors in this essay.

3.3. Data, Estimation and Structure Change

This chapter uses the same primary data as chapter 2 for the GMM estimation. As for the variables of X_{t+1} , Y_{t+1} , Z_{t+1} , and v_{t+1} , we use the primary data and corresponding estimates from GMM to generate new series, by substituting corresponding values into the definitions of those variables.

3.3.1. Stationary

To assure the validity of our analysis, we first test the stationarity of the residuals of the 4 time series used in our prediction matrix. Three unit root tests are performed on each of the four residuals and they are reported in table 3.1.

3.3.1.1. Augmented Dickey–Fuller test

The augmented Dickey–Fuller test tests whether a time series follows a unit-root process. The null hypothesis is that the series contains a unit root, and the alternative is that it was generated by a stationary process. The augmented Dickey–Fuller test first estimates model:

$$\Delta y_t = \alpha + \beta y_{t-1} + \delta t + \varsigma_1 \Delta y_{t-1} + \varsigma_2 \Delta y_{t-2} + \cdots + \varsigma_k \Delta y_{t-k} + \epsilon_t$$

and secondly tests the null hypothesis $H_0: \beta = 0$.

Dickey and Fuller (1979) proposed this unit root test, and Hamilton (1994, 28–529) described four different cases for its application. The null hypothesis is always that the variable has a unit root, but the variable may have a drift term, or the regression may include a constant term and time trend in different cases. We test the residuals in the fourth case, with no regression restrictions on drift or trend, because graph of the data shows an upward trend over time.

In the fourth case, the t-statistic used to test $H_0: \beta = 0$ does not have a standard distribution. The critical values reported by augmented Dickey–Fuller test are interpolated based on the tables in Fuller (1996). MacKinnon (1994) shows how to approximate the p-values on the basis of a regression surface, and augmented Dickey–Fuller test also reports that p-value.

Table 3.1. Unit Root Tests for Time Series Residuals

DF-GLS test with 1 lag					
	Statistic	Critical Value			p-value
		1%	5%	10%	
$\epsilon_{1,t+1}$	-8.645	-3.736	-3.177	-2.875	<0.01
$U_{2,t+1}$	-4.403	-3.736	-3.177	-2.875	<0.01
$\epsilon_{3,t+1}$	-3.016	-3.736	-3.177	-2.875	<0.01
$\epsilon_{4,t+1}$	-4.448	-3.736	-3.177	-2.875	<0.01

Augmented Dickey-Fuller test with 1 lag and trend						
		Statistic	Interpolated Dickey-Fuller Critical Value			p-value
			1%	5%	10%	
$\epsilon_{1,t+1}$	Z(t)	-10.211	-4.135	-3.493	-3.176	0.0000
$U_{2,t+1}$	Z(t)	-4.826	-4.135	-3.493	-3.176	0.0004
$\epsilon_{3,t+1}$	Z(t)	-5.534	-4.135	-3.493	-3.176	0.0000
$\epsilon_{4,t+1}$	Z(t)	-6.888	-4.135	-3.493	-3.176	0.0000

Phillips-Perron test						
		Statistic	Interpolated Dickey-Fuller Critical Value			p-value
			1%	5%	10%	
$\epsilon_{1,t+1}$	Z(rho)	-63.885	-19.044	-13.364	-10.748	0.0000
	Z(t)	-9.909	-3.569	-2.924	-2.597	
$U_{2,t+1}$	Z(rho)	-73.365	-19.044	-13.364	-10.748	0.0000
	Z(t)	-8.352	-3.569	-2.924	-2.597	
$\epsilon_{3,t+1}$	Z(rho)	-50.328	-19.044	-13.364	-10.748	0.0000
	Z(t)	-7.435	-3.569	-2.924	-2.597	
$\epsilon_{4,t+1}$	Z(rho)	-73.04	-19.044	-13.364	-10.748	0.0000
	Z(t)	-11.396	-3.569	-2.924	-2.597	

Note: $\epsilon_{i,t+1}$ and $U_{2,t+1}$ are residuals estimated in time series:

$$X_{t+1} = a_1 + b_1 X_t + \epsilon_{1,t+1} \quad (3.6)$$

$$p_{t+1} = [(p_t + v_t) - U_{2,t+1}] / [\beta' \left(\frac{y_t}{y_{t+1}} \right)^{1-\rho} \left(\frac{q_t}{q_{t+1}} \right)] - (\zeta \frac{\pi_{t+1}}{a_t} + v_{t+1}) \quad (3.3)$$

$$Z_{t+1} = a_3 + b_3 Z_t + \epsilon_{3,t+1} \quad (3.7)$$

$$v_{t+1} = a_4 + b_4 v_t + \epsilon_{4,t+1} \quad (3.8)$$

Equation (3.6), (3.7), and (3.8) are estimated with OLS in Stata11.

Equation (3.3) is estimated with Two-Stage GMM in Eview7.

3.3.1.2. DF-GLS test

DF-GLS is a modified Dickey–Fuller t test proposed by Elliott, Rothenberg, and Stock (1996). The main difference between DF-GLS test and an augmented Dickey–Fuller test is that the time series is transformed via a generalized least squares (GLS) regression before it is used in the DF-GLS test. DF-GLS test has been proved to have significantly greater power than the previous versions of the augmented Dickey–Fuller test.

DF-GLS test performs the test for the series of models that include 1 to k lags of the first differenced and detrended variable, and researchers have proposed approaches on how to set the value of k (Schwert 1989; Stock and Watson 2007). The null hypothesis of DG-GLS test is that y_t is a random walk possibly with a drift, and the alternative hypotheses is that y_t is stationary, with or without a linear time trend.

3.3.1.3. Phillips–Perron unit-root test

The Dickey–Fuller test estimates model

$$y_t = \alpha + \rho y_{t-1} + \delta t + u_t$$

by ordinary least squares (OLS), but serial correlation presents a problem in the estimation. The Phillips–Perron test uses Newey and West (1987) standard errors to account for serial correlation, whereas the augmented Dickey–Fuller test uses additional lags of the first-differenced variable y_t . Phillips and Perron’s test statistics can be viewed as Dickey–Fuller statistics that have been made robust to serial correlation by using the

Newey–West (1987) heteroskedasticity- and autocorrelation-consistent covariance matrix estimator.

The Phillips–Perron test applies to three cases (1, 2, and 4, but not 3) out of the four applicable cases of augmented Dickey–Fuller test. Since Case three, which assumes that the variable has a random walk with drift under the null hypothesis, is just a special case of case four (random walk with or without a drift), the fact that the Phillips–Perron test does not apply to case 3 is not restrictive.

As we can see in table 3.1, the nonstationarity null hypotheses for the residuals of 4 time series regressions are all rejected with 1 lag in the Dick-Fuller and Phillips-Perron tests at a significance level of 1%. These results rule out cointegration and therefore spurious correlations in our regressions (Engle and Granger 1987).

3.3.2. Stability

Regression analysis of time-series data usually adopts the assumption of stability or constancy of the regression relationship during the period of study, but this assumption is not always supported by data in the analysis. Therefore, before we study the value of economic information in predictions of farmland prices, we should first check the stability of the regression coefficients. The land price is estimated from equation (3.3)

$$p_{t+1} = [(p_t + v_t) - U_{2,t+1}]/[\beta' \left(\frac{y_t}{y_{t+1}}\right)^{1-\rho} \left(\frac{q_t}{q_{t+1}}\right)] - (\zeta \frac{\pi_{t+1}}{a_t} + v_{t+1}) \quad (3.3)$$

Two types of stability tests are performed on the coefficients in the CAPM model. First, we run the CUSUM and CUSUM squared tests (Brown, Durbin, and Evans 1975)

without specifying break points. Second, we run three GMM breakpoint tests at the potential breakpoints suggested in the CUSUM and CUSUM squared tests.

3.3.2.1. CUSUM and CUSUM squared tests

Brown, Durbin, and Evans (1975) described a set of techniques for detecting departures from constancy of regression relationships of time-series variables over time. The CUSUM test (Brown, Durbin, and Evans 1975) is based on the cumulative sum of the recursive residuals. This technique plots the cumulative sum together with the critical lines at a certain significance level. The test finds parameter instability if the cumulative sum goes outside the area between the two critical lines. The CUSUM test is based on the statistic:

$$W_r = \frac{1}{\hat{\sigma}} \sum_{j=k+1}^r w_j$$

for $r = k+1, \dots, T$, where W_r is the recursive residual defined above, and $\hat{\sigma}$ is the estimated standard deviation of the recursive residuals. If the β vector remains constant from period to period, $E(W_r) = 0$. If β vector changes, W_r will tend to diverge from the zero mean value line. So movement of W_r outside the critical lines is suggestive of coefficient instability. The 10% significance lines are found by connecting the points:

$[k, \pm 0.85 * \text{sqrt}(T-k)]$ and $[T, \pm 3 * 0.85 * \text{sqrt}(T-k)]$

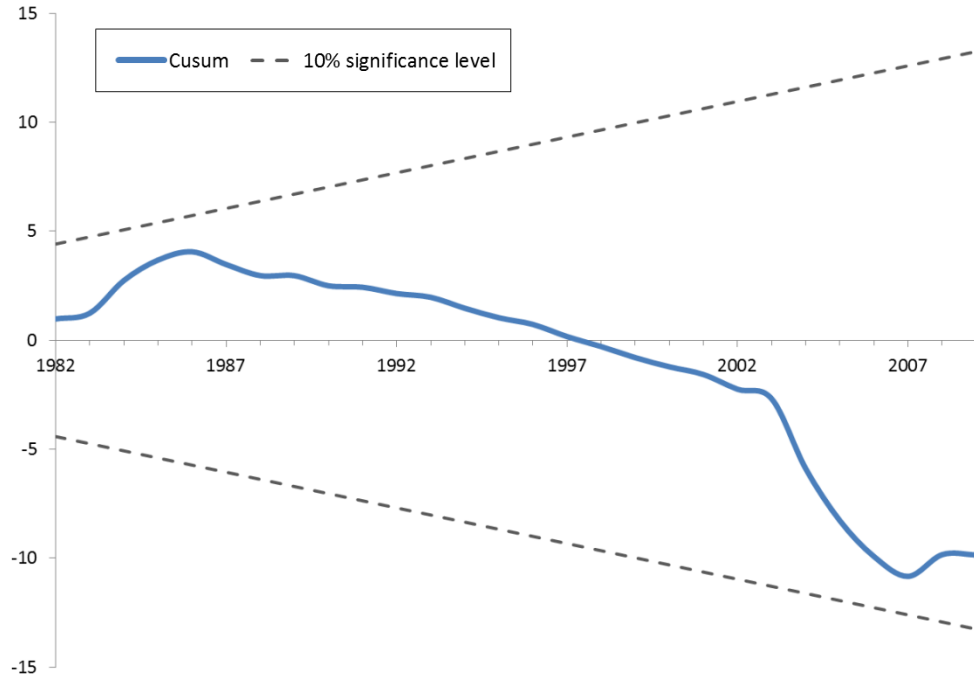


Figure 3.1. CUSUM Test of P_{t+1} at Significance Level of 10%

Note: CUSUM is calculated as: $W_r = \frac{1}{\hat{\sigma}} \sum_{j=k+1}^r w_j$
 $\hat{\sigma}$ is the estimated standard deviation of the recursive residuals $U_{2,t+1}$.
 $U_{2,t+1}$ are residuals estimated in time series with Two-stage GMM in Eview7:

$$p_{t+1} = [(p_t + v_t) - U_{2,t+1}] / [\beta' \left(\frac{y_t}{y_{t+1}} \right)^{1-\rho} \left(\frac{q_t}{q_{t+1}} \right)] - (\zeta \frac{\pi_{t+1}}{a_t} + v_{t+1}) \quad (3.3)$$

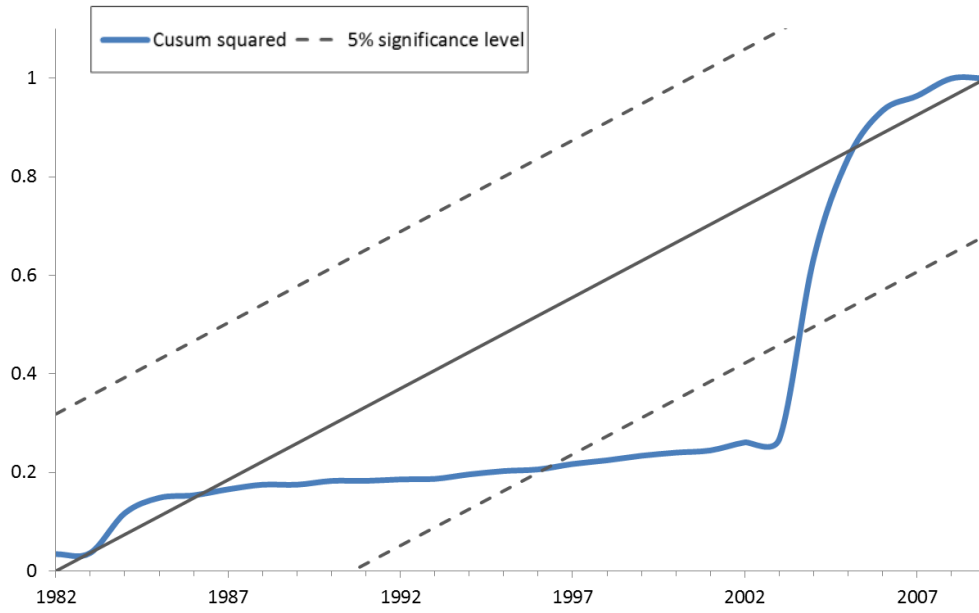


Figure 3.2. CUSUM Squared Test of P_{t+1} at Significance Level of 5%

Note: CUSUM is calculated as: $s_r = S_r/S_T = (\sum_{j=k+1}^r w_j^2)/(\sum_{j=k+1}^T w_j^2)$
 w_j^2 are the estimated residuals squared of the recursive residuals $U_{2,t+1}$.
 $U_{2,t+1}$ are residuals estimated in time series with Two-stage GMM in Eview7:

$$p_{t+1} = [(p_t + v_t) - U_{2,t+1}]/[\beta' \left(\frac{y_t}{y_{t+1}}\right)^{1-\rho} \left(\frac{q_t}{q_{t+1}}\right)] - (\zeta \frac{\pi_{t+1}}{a_t} + v_{t+1}) \quad (3.3)$$

As we can see in figure 3.1, the fact that the CUSUM test results do not move outside the critical values does not provide evidence of instability of coefficients in the CAPM model at 10% significance level. However, the sign changes in the figure suggest possible breakpoints at 1987 and 2007 during the period.

Brown, Durbin, and Evans (1975) also proposed the CUSUM of squares test, and it is based on the test statistic:

$$s_r = S_r/S_T = (\sum_{j=k+1}^r w_j^2)/(\sum_{j=k+1}^T w_j^2), r = k + 1, \dots, T$$

The expected value of s_r under the hypothesis of parameter constancy is:

$$E(s_r) = (r - k)/(T - k)$$

which goes from zero at $r = k$ to unity at $r = T$.

As we can see in figure 3.2, the CUSUM of squares test provides a plot of s_r against r and the pair of 5% critical lines parallel around the expected value. As with the CUSUM test, movement outside the critical lines is suggestive of parameter or variance instability. The significance of the departure of s_r from its expected value is assessed by reference to the critical lines according to relevant studies (Durbin 1969; Brown, Durbin, and Evans 1975; Johnston and DiNardo 1997). The CUSUM of squares test on p_{t+1} shows that there is a structure change in farmland prices estimation at 1997 in the CAPM model at 5% significance level.

As we can see in figure 3.3, both the nominal and real farmland prices turned around in the year of 1987, going out of the shadow of the farm crisis of the mid-1980s. After 1987, real farmland prices increased persistently: between 2 and 4 percent annually between 1994 and 2004, 16 and 11 percent in 2005 and 2006, and 6-7 percent in 2007

and 2008 (Nickerson et al 2012). This persistent rise drives farmland prices further and further away from its capital formula valuations.

The 1996 farm bill brought the "freedom to farm" reforms, remodeling counterproductive outdated agriculture programs originated in the Depression era. The most important accomplishment of the 1996 farm bill was to end the annual acreage reduction programs (ARPs), which severely restricted the ability of U.S. farmers to produce for the world marketplace, and depressed the rural economy (Frydenlund 2002). Since 1997 the amount of acreage rented by U.S. farmers has remained below 40 percent, meaning a higher ownership acreage in the U.S. farm sector. In other words, the 1996 farm bill may have caused a boom in farmland prices through enhanced demand of farmland in production.

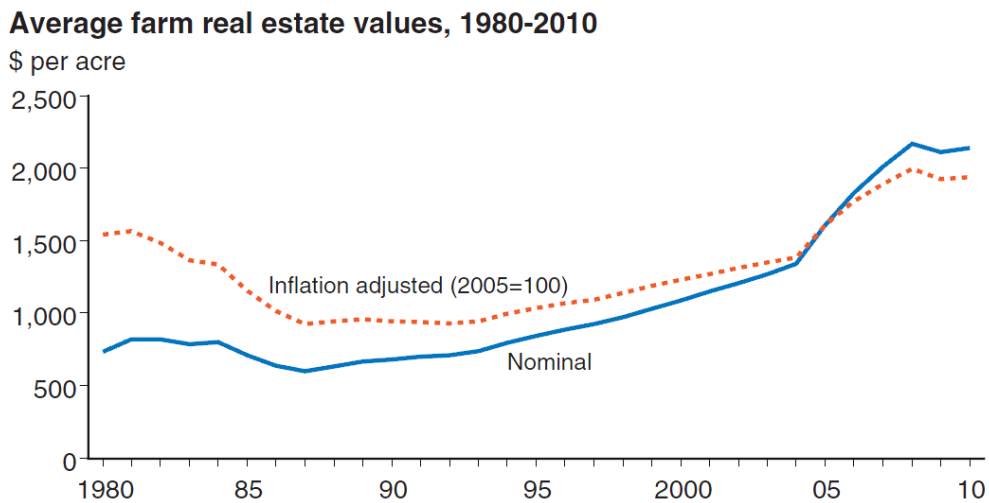


Figure 3.3. Observed Farmland Prices of Pt+1 during the Period of 1980-2010

Note: USDA data are cited as in Nickerson et al, 2012
Source: USDA, National Agricultural Statistics Services, 2012

3.3.2.2 GMM breakpoint tests

According to the graphs of CUSUM and CUSUM of squares tests, we test the stability at two time spots and find instability in both years of 1987 and 1997, as we can see in table 3.2.

Table 3.2. GMM Breakpoint Tests for p_{t+1}

	1987		1997	
	Test Statistic	p-Value	Test Statistic	p-Value
Andrews-Fair Wald	$\chi^2(5) =$	-	$\chi^2(5) =$	-
Andrews-Fair LR-type D	$\chi^2(5) = 9.24\text{E-}14$	0.9999	$\chi^2(5) = -7.82\text{E-}14$	-
Hall and Sen O	$\chi^2(3) = 13.0497$	0.0423	$\chi^2(3) = 16.0568$	0.0135

Note: GMM breakpoint tests are performed on the estimation of p_{t+1} as in:

$$p_{t+1} = [(p_t + v_t) - U_{2,t+1}]/[\beta' \left(\frac{y_t}{y_{t+1}}\right)^{1-\rho} \left(\frac{q_t}{q_{t+1}}\right)] - (\zeta \frac{\pi_{t+1}}{a_t} + v_{t+1}) \quad (3.3)$$

The test statistics are calculated as:

$$\text{Andrews-Fair Wald: } AF_1 = (\theta_1 - \theta_2)' \left(\frac{1}{T_1} V_1^{-1} + \frac{1}{T_2} V_2^{-1} \right)^{-1} (\theta_1 - \theta_2)$$

$$\text{Andrews-Fair LR-type D: } AF_2 = J_R - (J_1 + J_2)$$

$$\text{Hall and Sen O: } O_T = J_1 + J_2$$

The GMM Breakpoint test is similar to the Chow Breakpoint Test, but it is geared towards equations estimated via GMM rather than least squares. We calculate three different types of GMM breakpoint test statistics: the Andrews and Fair (1988) Wald Statistic, the Andrews-Fair LR-type Statistic, and the Hall and Sen (1999) O-Statistic. The first two statistics test the null hypothesis that there are no structural breaks in the equation parameters, while the third statistic tests breaks in the over-identifying restrictions. All three test statistics have an asymptotic χ^2 distribution: the first two with $(m-1)k$ degrees of freedom, and O-statistic with $2*(q-(m-1)k)$ degrees of freedom. m is

the number of subsamples, k is the number of coefficients in the original equation, and q is the number of time series in the equation.

Similar to the Chow Statistics, the data are partitioned into different subsamples, and the equation is re-estimated for each subsample to calculate the GMM breakpoint test statistics. The major difference between the GMM breakpoint test and the Chow test procedures is that the Chow Statistic is calculated with constant variance-covariance matrix of the error terms of the entire sample, but the GMM breakpoint statistic allows the variance-covariance matrix of the error terms vary between the subsamples. The Andrews-Fair Wald test for single breakpoint is based on the test statistic:

$$AF_1 = (\theta_1 - \theta_2)' \left(\frac{1}{T_1} V_1^{-1} + \frac{1}{T_2} V_2^{-1} \right)^{-1} (\theta_1 - \theta_2)$$

where

θ_i = the coefficient estimates from subsample i ,

T_i = the number of observations in subsample i ,

V_i = the estimate of the variance-covariance matrix for subsample i .

The Andrews-Fair LR-type statistic is a comparison of the J-statistics:

$$AF_2 = J_R - (J_1 + J_2)$$

where

J_i = the J-statistics estimates from subsample i ,

J_R = the J-statistics calculated with the original equation's residuals, and a combined GMM weighting matrix that equals the weighted (by number of observations) sum of the estimated weighting matrices from each of the subsample estimations.

The Hall and Sen O-Statistic is calculated as:

$$O_T = J_1 + J_2$$

As we can see in table 3.2, the Andrews-Fair Wald Statistic and the Andrews-Fair LR-type Statistic fail to provide evidence of the parameter breakpoints in 1987 or 1997. The Hall and Sen O-Statistic shows breakpoints in overidentifying restrictions in both 1987 and 1997 at 5% significance level.

After generating new time series variables as defined in Section II, we test the stationarity and stability of the regressions used for forecasting in this Section. All 4 residuals pass the stationarity tests and this reinforces the validity of our analysis. However, the stability tests show 2 significant breakpoints in the GMM estimation. Therefore, we define 3 stages in the studied period accordingly:

- a. 1982~1987 busting stage
- b. 1988~1997 stable stage
- c. 1998~2009 booming stage

Here we follow Falk (1991) on the definition of different stages. Falk (1991) tested the present value model with Iowa farmland price and rent data during the period of 1921-1986. He found that price movements are not always consistent with the implications of the present value model, and there are persistent predictable excess positive and negative returns in the farmland market. We define the stage when the farmland prices are persistently higher than the implication of the present value model as a booming stage, persistently lower as a busting stage, and consistent as a stable stage. In this chapter we follow the agricultural economics literature and refer to the three stages

of land prices as “boom”, “bust”, and “stable” (Schmitz 1995). Further research relating these notions to the mathematics of the Characteristic equation (Box and Jenkins 1976) is certainly worthwhile.

The following sections will study the forecast errors in each stage and compare them to evaluate the economic information in predictions of farmland prices in different scenarios.

3.4. Forecast Error Variance Decomposition Procedure

As discussed in Section I, we adopt the Forecast Error Variance Decomposition (FEVD) procedure to study the QRE predictions. In this section, we study the forecast error variance of Y_t and P_t , farmland price, in different stages over time. Three typical steps are taken to obtain FEVD. First, we write out the impulse response functions in the matrix form, second, we write out the moving average representation of forecast errors, and third, we calculate the forecast error variance decomposition for CAPM impacts.

3.4.1. Impulse Response

First, Impulse responses for errors in X_t , Y_t , and Z_t are calculated for equation (3.13), the nonlinear matrix form developed in Section II (Koop, Pesaran, and Potter 1996; Potter 2000). We denote the impulse response function of X_t , Y_t , and Z_t as a 3 by 3 matrix $[\Theta]$.

3.4.1.1. Column 1, $[\Theta]_1$

First, we write out the three elements in column 1, $[\Theta]_1$ for 3 periods.

$$d\epsilon_{1,t+1} = \Delta, dU_{2,t+1} = 0, d\epsilon_{3,t+1} = 0$$

$$\Rightarrow d\epsilon_{2,t+1} = d[\zeta\epsilon_{1,t+1} + Y_t\epsilon_{3,t+1} - U_{2,t+1}(a_3 + b_3Z_t + \epsilon_{3,t+1})] = \zeta\Delta$$

$$\Rightarrow [\Theta_0]_1 d\epsilon_{1,t+1} = d \begin{bmatrix} X_{t+1} \\ Y_{t+1} \\ Z_{t+1} \end{bmatrix} = \begin{bmatrix} b_1 & 0 & 0 \\ \zeta b_1 & a_3 + b_3Z_t & b_3Y_t \\ 0 & 0 & b_3 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} + \Delta \begin{bmatrix} 1 \\ \zeta \\ 0 \end{bmatrix} = \Delta \begin{bmatrix} 1 \\ \zeta \\ 0 \end{bmatrix} \quad (3.15a)$$

$$\Rightarrow [\Theta_1]_1 d\epsilon_{1,t+1} = d \begin{bmatrix} X_{t+2} \\ Y_{t+2} \\ Z_{t+2} \end{bmatrix} = \Delta \begin{bmatrix} b_1 & 0 & 0 \\ \zeta b_1 & a_3 + b_3Z_t & b_3Y_t \\ 0 & 0 & b_3 \end{bmatrix} \begin{bmatrix} 1 \\ \zeta \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} = \Delta \begin{bmatrix} b_1 \\ \zeta b_1 + (a_3 + b_3Z_t)\zeta \\ 0 \end{bmatrix} \quad (3.15b)$$

$$\Rightarrow [\Theta_2]_1 d\epsilon_{1,t+1} = d \begin{bmatrix} X_{t+3} \\ Y_{t+3} \\ Z_{t+3} \end{bmatrix} = \Delta \begin{bmatrix} b_1 & 0 & 0 \\ \zeta b_1 & a_3 + b_3Z_t & b_3Y_t \\ 0 & 0 & b_3 \end{bmatrix} \begin{bmatrix} b_1 \\ (b_1 + a_3 + b_3Z_t)\zeta \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} = \Delta \begin{bmatrix} b_1^2 \\ \zeta b_1^2 + (a_3 + b_3Z_t)(b_1 + a_3 + b_3Z_t)\zeta \\ 0 \end{bmatrix} \quad (3.15c)$$

3.4.1.2. Column 2, $[\Theta]_2$

Second, we write out the three elements in column 2, $[\Theta]_2$ for 3 periods.

$$d\epsilon_{1,t+1} = 0, dU_{2,t+1} = \Delta, d\epsilon_{3,t+1} = 0$$

$$\Rightarrow d\epsilon_{2,t+1} = d[\zeta\epsilon_{1,t+1} + Y_t\epsilon_{3,t+1} - U_{2,t+1}(a_3 + b_3Z_t + \epsilon_{3,t+1})] = -\Delta(a_3 + b_3Z_t)$$

$$\Rightarrow [\Theta_0]_{,2}d\epsilon_{2,t+1} = d \begin{bmatrix} X_{t+1} \\ Y_{t+1} \\ Z_{t+1} \end{bmatrix} =$$

$$\begin{bmatrix} b_1 & 0 & 0 \\ \zeta b_1 & a_3 + b_3Z_t & b_3Y_t \\ 0 & 0 & b_3 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} + \Delta \begin{bmatrix} 0 \\ -(a_3 + b_3Z_t) \\ 0 \end{bmatrix} = \Delta \begin{bmatrix} 0 \\ -(a_3 + b_3Z_t) \\ 0 \end{bmatrix} \quad (3.16a)$$

$$\Rightarrow [\Theta_1]_{,2}d\epsilon_{2,t+1} = d \begin{bmatrix} X_{t+2} \\ Y_{t+2} \\ Z_{t+2} \end{bmatrix} = \Delta \begin{bmatrix} b_1 & 0 & 0 \\ \zeta b_1 & a_3 + b_3Z_t & b_3Y_t \\ 0 & 0 & b_3 \end{bmatrix} \begin{bmatrix} 0 \\ -(a_3 + b_3Z_t) \\ 0 \end{bmatrix} +$$

$$\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} = \Delta \begin{bmatrix} 0 \\ -(a_3 + b_3Z_t)^2 \\ 0 \end{bmatrix} \quad (3.16b)$$

$$\Rightarrow [\Theta_2]_{,2}d\epsilon_{2,t+1} = d \begin{bmatrix} X_{t+3} \\ Y_{t+3} \\ Z_{t+3} \end{bmatrix} = \Delta \begin{bmatrix} b_1 & 0 & 0 \\ \zeta b_1 & a_3 + b_3Z_t & b_3Y_t \\ 0 & 0 & b_3 \end{bmatrix} \begin{bmatrix} 0 \\ -(a_3 + b_3Z_t)^2 \\ 0 \end{bmatrix} +$$

$$\begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} = \Delta \begin{bmatrix} 0 \\ -(a_3 + b_3Z_t)^3 \\ 0 \end{bmatrix} \quad (3.16c)$$

3.4.1.3. Column 3, $[\Theta]_{,3}$

Third, we write out the three elements in column 3, $[\Theta]_{,3}$ for 3 periods.

$$d\epsilon_{1,t+1} = 0, \quad dU_{2,t+1} = 0, \quad d\epsilon_{3,t+1} = \Delta$$

$$\Rightarrow d\epsilon_{2,t+1} = d[\zeta\epsilon_{1,t+1} + Y_t\epsilon_{3,t+1} - U_{2,t+1}(a_3 + b_3Z_t + \epsilon_{3,t+1})] = \Delta Y_t$$

$$\Rightarrow [\Theta_0]_{,3} d\epsilon_{3,t+1} = d \begin{bmatrix} X_{t+1} \\ Y_{t+1} \\ Z_{t+1} \end{bmatrix} = \begin{bmatrix} b_1 & 0 & 0 \\ \zeta b_1 & a_3 + b_3 Z_t & b_3 Y_t \\ 0 & 0 & b_3 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} + \Delta \begin{bmatrix} 0 \\ Y_t \\ 1 \end{bmatrix} = \Delta \begin{bmatrix} 0 \\ Y_t \\ 1 \end{bmatrix} \quad (3.17a)$$

$$\Rightarrow [\Theta_1]_{,3} d\epsilon_{3,t+1} = d \begin{bmatrix} X_{t+2} \\ Y_{t+2} \\ Z_{t+2} \end{bmatrix} = \Delta \begin{bmatrix} b_1 & 0 & 0 \\ \zeta b_1 & a_3 + b_3 Z_t & b_3 Y_t \\ 0 & 0 & b_3 \end{bmatrix} \begin{bmatrix} 0 \\ Y_t \\ 1 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} =$$

$$\Delta \begin{bmatrix} 0 \\ (a_3 + b_3 Z_t + b_3) Y_t \\ b_3 \end{bmatrix} \quad (3.17b)$$

$$\Rightarrow [\Theta_2]_{,3} d\epsilon_{3,t+1} = d \begin{bmatrix} X_{t+3} \\ Y_{t+3} \\ Z_{t+3} \end{bmatrix} =$$

$$\Delta \begin{bmatrix} b_1 & 0 & 0 \\ \zeta b_1 & a_3 + b_3 Z_t & b_3 Y_t \\ 0 & 0 & b_3 \end{bmatrix} \begin{bmatrix} 0 \\ (a_3 + b_3 Z_t + b_3) Y_t \\ b_3 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} =$$

$$\Delta \begin{bmatrix} 0 \\ (a_3 + b_3 Z_t)(a_3 + b_3 Z_t + b_3) Y_t + b_3^2 Y_t \\ b_3^2 \end{bmatrix} \quad (3.17c)$$

3.4.2. Moving Average Representation of Forecast Error

Next, the forecast error of Y_{t+1} is written out with the error terms of X_t , Y_t , and Z_t according to impulse responses functions specified in section 3.4.1. (Swanson and Granger 1997).

3.4.2.1. Write out Forecast Error Terms

We denote a venter as V_{t+1} and its forecast as V_{t+1}^f , so the forecast error, FE_{t+1} , is the difference between V_{t+1} and V_{t+1}^f .

$$V_{t+1} = \Theta_0 \epsilon_{t+1} + \Theta_1 \epsilon_t + \Theta_2 \epsilon_{t-1} + \Theta_3 \epsilon_{t-2} + \dots \quad (3.18a)$$

$$V_{t+1}^f = \Theta_0 (\epsilon_{t+1}^f = 0) + \Theta_1 \epsilon_t + \Theta_2 \epsilon_{t-1} + \Theta_3 \epsilon_{t-2} + \dots \quad (3.18b)$$

$$FE_{t+1} = \Theta_0 \epsilon_{t+1} \quad (3.19a)$$

$$FE_{t+2} = \Theta_0 \epsilon_{t+2} + \Theta_1 \epsilon_{t+1} \quad (3.19b)$$

$$FE_{t+3} = \Theta_0 \epsilon_{t+3} + \Theta_1 \epsilon_{t+2} + \Theta_2 \epsilon_{t+1} \quad (3.19c)$$

3.4.2.2 Zero One Simulation of the MA Representation

In order to specify the MA representation for decomposition, we substitute the impulse response function, [equation (3.15), equation (3.16), equation (3.17)], into equation (3.19).

$$FE_{t+1} = \Theta_0 \epsilon_{t+1} = \begin{bmatrix} \epsilon_{1,t+1} \\ \zeta \epsilon_{1,t+1} - (a_3 + b_3 Z_t) \epsilon_{2,t+1} + Y_t \epsilon_{3,t+1} \\ \epsilon_{3,t+1} \end{bmatrix} \quad (3.20a)$$

$$\begin{aligned} FE_{t+2} = \Theta_0 \epsilon_{t+2} + \Theta_1 \epsilon_{t+1} = & \begin{bmatrix} \epsilon_{1,t+2} \\ \zeta \epsilon_{1,t+2} - (a_3 + b_3 Z_t) \epsilon_{2,t+2} + Y_t \epsilon_{3,t+2} \\ \epsilon_{3,t+2} \end{bmatrix} \\ & + \begin{bmatrix} b_1 \epsilon_{1,t+1} \\ [\zeta b_1 + (a_3 + b_3 Z_t) \zeta] \epsilon_{1,t+1} - (a_3 + b_3 Z_t)^2 \epsilon_{2,t+1} + (a_3 + b_3 Z_t + b_3) Y_t \epsilon_{3,t+1} \\ b_3 \epsilon_{3,t+1} \end{bmatrix} \end{aligned} \quad (3.20b)$$

$$FE_{t+3} = \Theta_0 \epsilon_{t+3} + \Theta_1 \epsilon_{t+2} + \Theta_2 \epsilon_{t+1} = \begin{bmatrix} \epsilon_{1,t+3} \\ \zeta \epsilon_{1,t+3} - (a_3 + b_3 Z_t) \epsilon_{2,t+3} + Y_t \epsilon_{3,t+3} \\ \epsilon_{3,t+3} \end{bmatrix}$$

$$\begin{aligned}
& + \left[\begin{array}{c} b_1 \epsilon_{1,t+2} \\ [\zeta b_1 + (a_3 + b_3 Z_t) \zeta] \epsilon_{1,t+2} - (a_3 + b_3 Z_t)^2 \epsilon_{2,t+2} + (a_3 + b_3 Z_t + b_3) Y_t \epsilon_{3,t+2} \\ b_3 \epsilon_{3,t+2} \end{array} \right] \\
& + \left[\begin{array}{c} b_1^2 \epsilon_{1,t+1} \\ [\zeta b_1^2 + (a_3 + b_3 Z_t)(b_1 + a_3 + b_3 Z_t) \zeta] \epsilon_{1,t+1} - (a_3 + b_3 Z_t)^3 \epsilon_{2,t+1} \\ b_3^2 \epsilon_{3,t+1} \end{array} \right]_{2.1} + \\
& \left[\begin{array}{c} [(a_3 + b_3 Z_t)(a_3 + b_3 Z_t + b_3) Y_t + b_3^2 Y_t] \epsilon_{3,t+1} \end{array} \right]_{2.2} \\
& \tag{3.20c}
\end{aligned}$$

The deduction details could be found in Appendix E.

3.4.3. Forecast Error Variance Decomposition

Finally, we decompose the forecast error of Y_{t+1} and p_{t+1} . Quasi-rational expectation forecasts are generated from the general DLPM developed in Chapter 2 using the chain rule. By definition, both the short-run and long-run forecast error variance decompositions sum to 100%. The coefficients and residuals used in the calculation are reported in table 3.4. Since we do not orthogonalize the data, we include the correlations significant at 5% level. The residuals correlations and their p-values are

Table 3.3. Correlations between Residuals in the Recursive Estimations

Year		ρ_{12}	ρ_{13}	ρ_{14}	ρ_{23}	ρ_{24}	ρ_{34}
1982	Correlation	-0.2779	0.4067	0.0587	-0.2497	-0.6020	-0.1072
	P-value	0.1236	0.0209	0.7495	0.1682	0.0003	0.5593
1983	Correlation	-0.1090	0.4548	-0.0016	0.1480	-0.6546	-0.4166
	P-value	0.5460	0.0078	0.9928	0.4112	0.0000	0.0159
1984	Correlation	-0.2365	0.3551	0.0794	-0.2410	-0.6394	-0.1876
	P-value	0.1780	0.0393	0.6553	0.1698	0.0000	0.2879
1985	Correlation	0.0192	0.2454	0.0087	-0.2050	-0.4097	-0.2932
	P-value	0.9130	0.1553	0.9603	0.2375	0.0145	0.0874
1986	Correlation	-0.0186	0.2904	0.0272	-0.1301	-0.6384	-0.2964
	P-value	0.9144	0.0857	0.8747	0.4496	0.0000	0.0792
1987	Correlation	0.0788	0.2998	-0.0414	0.0515	-0.6420	-0.3480
	P-value	0.6428	0.0714	0.808	0.7620	0.0000	0.0348
1988	Correlation	0.0321	0.2976	-0.0307	0.0660	-0.6253	-0.1855
	P-value	0.8484	0.0696	0.8548	0.6939	0.0000	0.2647
1989	Correlation	0.0269	0.3015	-0.0525	0.0576	-0.6144	-0.2452
	P-value	0.8709	0.0622	0.7512	0.7277	0.0000	0.1325
1990	Correlation	0.0622	0.3278	-0.0105	0.0720	-0.6161	-0.1576
	P-value	0.7032	0.0390	0.9486	0.6586	0.0000	0.3316
1991	Correlation	0.0445	0.3096	-0.0072	0.0878	-0.6410	-0.1189
	P-value	0.7825	0.0489	0.9643	0.5852	0.0000	0.4589
1992	Correlation	0.0214	0.3222	0.0344	-0.2102	-0.5942	-0.0934
	P-value	0.8929	0.0374	0.8288	0.1816	0.0000	0.5563
1993	Correlation	0.0695	0.3053	-0.0831	-0.0237	-0.6443	-0.3181
	P-value	0.6577	0.0465	0.5961	0.8799	0.0000	0.0376
1994	Correlation	0.1207	0.3002	-0.0609	-0.0320	-0.6187	-0.2998
	P-value	0.4352	0.0477	0.6947	0.8364	0.0000	0.0480
1995	Correlation	0.0539	0.2734	-0.0655	-0.0297	-0.6307	-0.3068
	P-value	0.7253	0.0692	0.6692	0.8463	0.0000	0.0404
1996	Correlation	0.0586	0.2845	-0.0542	-0.0261	-0.6269	-0.2908
	P-value	0.6988	0.0553	0.7208	0.8635	0.0000	0.0499
1997	Correlation	0.0665	0.2855	-0.0604	-0.0077	-0.6462	-0.2978
	P-value	0.6568	0.0517	0.6869	0.9588	0.0000	0.0420
1998	Correlation	0.0707	0.2841	-0.0572	-0.0116	-0.6311	-0.2906
	P-value	0.6332	0.0503	0.6992	0.9375	0.0000	0.0451
1999	Correlation	0.0738	0.2786	-0.0697	0.0071	-0.6201	-0.3012
	P-value	0.6142	0.0526	0.6344	0.9616	0.0000	0.0355
2000	Correlation	0.0651	0.2747	-0.0904	0.0407	-0.6354	-0.3152
	P-value	0.6533	0.0535	0.5324	0.7792	0.0000	0.0258
2001	Correlation	0.0779	0.2872	-0.0694	0.0678	-0.6340	-0.3040
	P-value	0.5868	0.0410	0.6286	0.6362	0.0000	0.0301

Table 3.3. Continued

Year		ρ_{12}	ρ_{13}	ρ_{14}	ρ_{23}	ρ_{24}	ρ_{34}
2002	Correlation	0.0402	0.2574	-0.0772	0.1167	-0.5599	-0.2188
	P-value	0.7774	0.0654	0.5863	0.4098	0.0000	0.1191
2003	Correlation	0.0032	0.2639	-0.0497	0.1125	-0.6365	-0.2853
	P-value	0.9816	0.0562	0.7236	0.4226	0.0000	0.0384
2004	Correlation	0.0892	0.2325	-0.0089	-0.1821	-0.4149	0.0033
	P-value	0.5214	0.0907	0.9491	0.1876	0.0018	0.9813
2005	Correlation	0.2547	0.2444	-0.0153	-0.1421	-0.3541	0.0448
	P-value	0.0606	0.0722	0.9118	0.3006	0.0080	0.7453
2006	Correlation	0.0405	0.2650	-0.0217	0.0651	-0.5465	-0.2919
	P-value	0.7671	0.0484	0.8736	0.6336	0.0000	0.0290
2007	Correlation	0.0395	0.2226	-0.0517	0.0492	-0.4110	-0.2648
	P-value	0.7702	0.0960	0.7025	0.7164	0.0015	0.0465
2008	Correlation	0.0380	0.2613	-0.0299	0.0846	-0.1776	-0.1709
	P-value	0.7771	0.0476	0.8239	0.5276	0.1823	0.1995
2009	Correlation	0.0728	0.2893	0.0026	0.0730	-0.5986	-0.2146
	P-value	0.5838	0.0263	0.9847	0.5829	0.0000	0.1027

Note: ρ_{ij} is the correlation between residual $\epsilon_{i,t+1}$ and $\epsilon_{j,t+1}$ or $U_{j,t+1}$

$$X_{t+1} = a_1 + b_1 X_t + \epsilon_{1,t+1} \quad (3.6)$$

$$Y_{t+1} = Z_{t+1} Y_t + \zeta X_{t+1} - U_{2,t+1} Z_{t+1} \quad (3.5)$$

$$Z_{t+1} = a_3 + b_3 Z_t + \epsilon_{3,t+1} \quad (3.7)$$

$$v_{t+1} = a_4 + b_4 v_t + \epsilon_{4,t+1} \quad (3.8)$$

Equation (3.6), (3.7), and (3.8) are estimated with OLS in Stata11.

Equation (3.5) is estimated with Two-stage GMM in Eview7.

Table 3.4. The Values of Data, Coefficients, and Residuals Used in the Calculation of Forecast Variance Decomposition

Year	Y_t	Z_t	a_1	b_1	a_3	b_3	a_4	b_4	ζ	σ_1^2	σ_2^2	σ_3^2	σ_4^2
1982	0.8246	1.0906	0.0042	0.7241	0.2851	0.7300	-0.0011	0.6998	0.5411	0.0000	0.0026	0.0006	0.0010
1983	0.8068	1.0477	0.0049	0.6949	0.3695	0.6508	0.0193	0.3437	0.7582	0.0000	0.0012	0.0008	0.0004
1984	0.8298	1.0684	0.0045	0.7313	0.2417	0.7728	0.0088	0.6801	1.7787	0.0000	0.0051	0.0004	0.0022
1985	0.7256	1.0633	0.0040	0.7727	0.2402	0.7711	0.0090	0.4022	0.9375	0.0000	0.0012	0.0004	0.0001
1986	0.6809	1.0332	0.0031	0.8487	0.2682	0.7456	0.0203	0.5078	1.4341	0.0000	0.0022	0.0005	0.0008
1987	0.6475	1.0628	0.0027	0.8823	0.3807	0.6397	0.0396	0.2043	0.9075	0.0000	0.0028	0.0008	0.0009
1988	0.6760	1.0297	0.0018	0.9469	0.3366	0.6816	0.0550	0.0462	0.9490	0.0000	0.0034	0.0006	0.0013
1989	0.7030	1.0531	0.0019	0.9430	0.3659	0.6544	0.0548	0.0171	1.0005	0.0000	0.0032	0.0007	0.0011
1990	0.7169	1.0891	0.0025	0.9056	0.3789	0.6416	0.0447	0.1135	0.9179	0.0000	0.0029	0.0007	0.0010
1991	0.7491	1.0509	0.0018	0.9532	0.3862	0.6348	0.0366	0.2594	1.0985	0.0000	0.0031	0.0007	0.0012
1992	0.7190	1.0527	0.0021	0.9339	0.4026	0.6163	0.0020	0.6988	0.0882	0.0000	0.0045	0.0007	0.0015
1993	0.8053	1.0398	0.0018	0.9608	0.3800	0.6396	0.0223	0.4844	0.6408	0.0000	0.0024	0.0006	0.0009
1994	0.8157	1.0438	0.0027	0.9048	0.3891	0.6309	0.0177	0.5385	0.5485	0.0000	0.0023	0.0006	0.0008
1995	0.8670	1.0449	0.0021	0.9537	0.3805	0.6390	0.0203	0.5185	0.5226	0.0000	0.0024	0.0006	0.0009
1996	0.9130	1.0552	0.0026	0.9225	0.3776	0.6415	0.0192	0.5367	0.4982	0.0000	0.0024	0.0006	0.0009
1997	0.9462	1.0397	0.0028	0.9135	0.3796	0.6394	0.0225	0.5152	0.4277	0.0000	0.0026	0.0006	0.0011
1998	1.0017	1.0431	0.0027	0.9180	0.3802	0.6388	0.0199	0.5335	0.3966	0.0000	0.0024	0.0006	0.0009
1999	1.0559	1.0421	0.0026	0.9274	0.3767	0.6422	0.0221	0.4869	0.3630	0.0000	0.0023	0.0006	0.0009
2000	1.1193	1.0406	0.0024	0.9396	0.3755	0.6433	0.0315	0.3910	0.3436	0.0000	0.0027	0.0005	0.0011
2001	1.1780	1.0431	0.0030	0.9032	0.3845	0.6346	0.0350	0.3550	0.3244	0.0000	0.0029	0.0006	0.0012
2002	1.2268	1.0333	0.0028	0.9301	0.3857	0.6340	0.0477	0.0778	0.0778	0.0000	0.0027	0.0005	0.0010
2003	1.3148	1.0412	0.0015	1.0009	0.3962	0.6241	0.0592	0.1675	0.1675	0.0001	0.0041	0.0006	0.0018
2004	1.3252	1.0456	0.0024	0.9617	0.2724	0.7398	-0.0060	0.6573	0.0717	0.0001	0.0023	0.0003	0.0002
2005	1.5969	1.0424	0.0036	0.9076	0.3176	0.6971	-0.0053	0.6771	0.0423	0.0001	0.0027	0.0004	0.0002
2006	1.8557	1.0430	0.0032	0.9283	0.3897	0.6299	0.0445	0.3420	0.1764	0.0001	0.0050	0.0005	0.0018
2007	2.0500	1.0535	0.0026	0.9585	0.3265	0.6893	0.0385	0.2426	0.1086	0.0001	0.0037	0.0004	0.0010
2008	2.1808	1.0424	0.0038	0.9091	0.2597	0.7517	0.0300	0.1879	0.4159	0.0001	0.0036	0.0003	0.0005
2009	2.1003	1.0082	0.0034	0.9324	0.3141	0.7007	0.0459	0.4824	0.0875	0.0001	0.0075	0.0004	0.0038

Table 3.4. Continued

Note: Y_t and Z_t are new time series defined as: $Y_{t+1} \equiv (p_{t+1} + v_{t+1})$, and $Z_{t+1} \equiv \frac{1}{\beta'} \left(\frac{y_{t+1}}{y_t} \right)^{1-\rho} \left(\frac{q_{t+1}}{q_t} \right)$

a_i and b_i are coefficient estimates for exogenous variables:

$$X_{t+1} = a_1 + b_1 X_t + \epsilon_{1,t+1} \quad (3.6)$$

$$Z_{t+1} = a_3 + b_3 Z_t + \epsilon_{3,t+1} \quad (3.7)$$

$$v_{t+1} = a_4 + b_4 v_t + \epsilon_{4,t+1} \quad (3.8)$$

ζ is the coefficient estimate in CAPM model:

$$p_{t+1} = [(p_t + v_t) - U_{2,t+1}] / [\beta' \left(\frac{y_t}{y_{t+1}} \right)^{1-\rho} \left(\frac{q_t}{q_{t+1}} \right)] - (\zeta \frac{\pi_{t+1}}{a_t} + v_{t+1}) \quad (3.3)$$

σ_i^2 is the estimated variance of the residuals in the time series predictions above.

Estimated Coefficients for Exogenous Variables

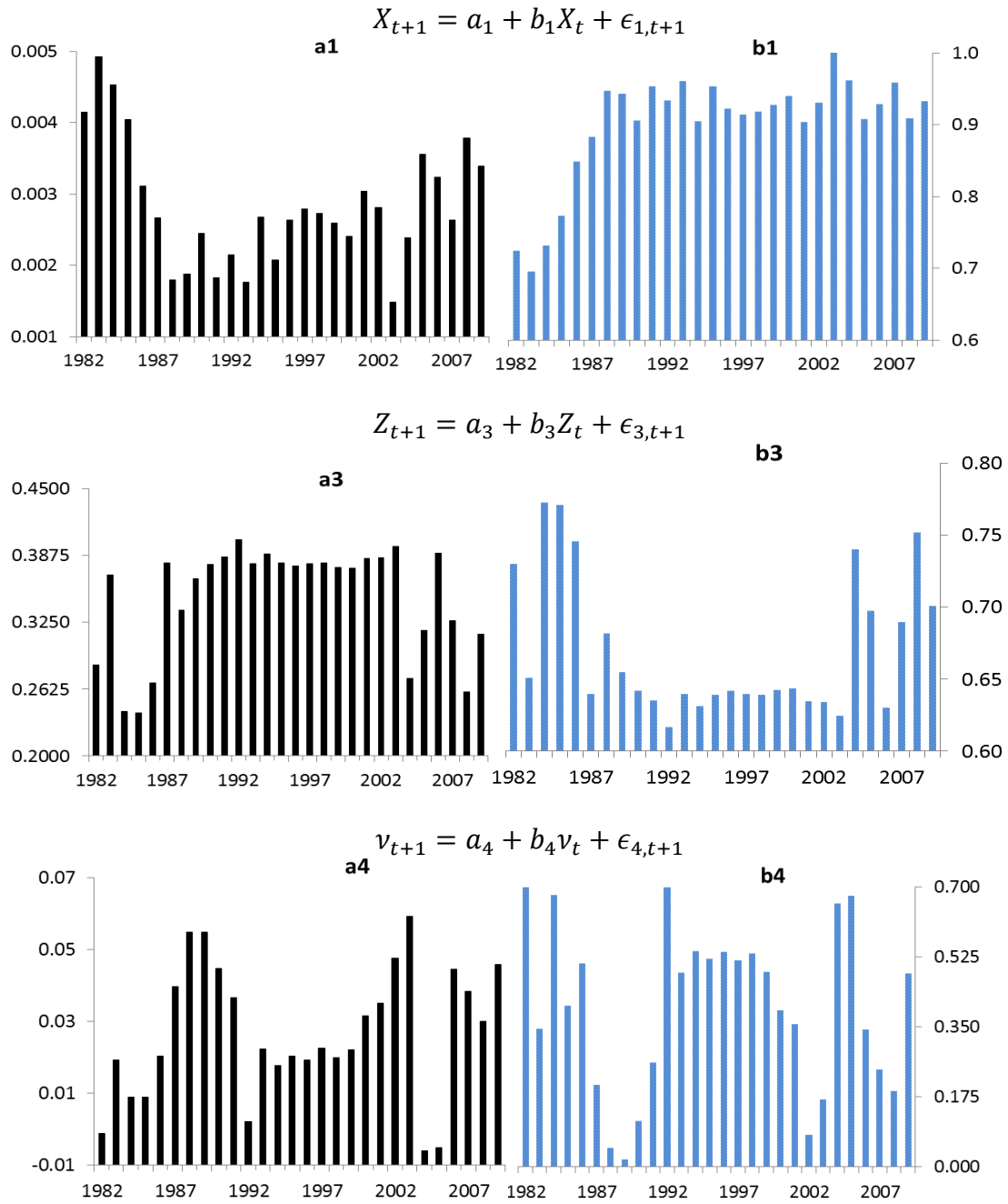


Figure 3.4. Estimated Coefficients for X_{t+1} , Z_{t+1} and v_{t+1} over Period 1950-1982 to 1950-2009

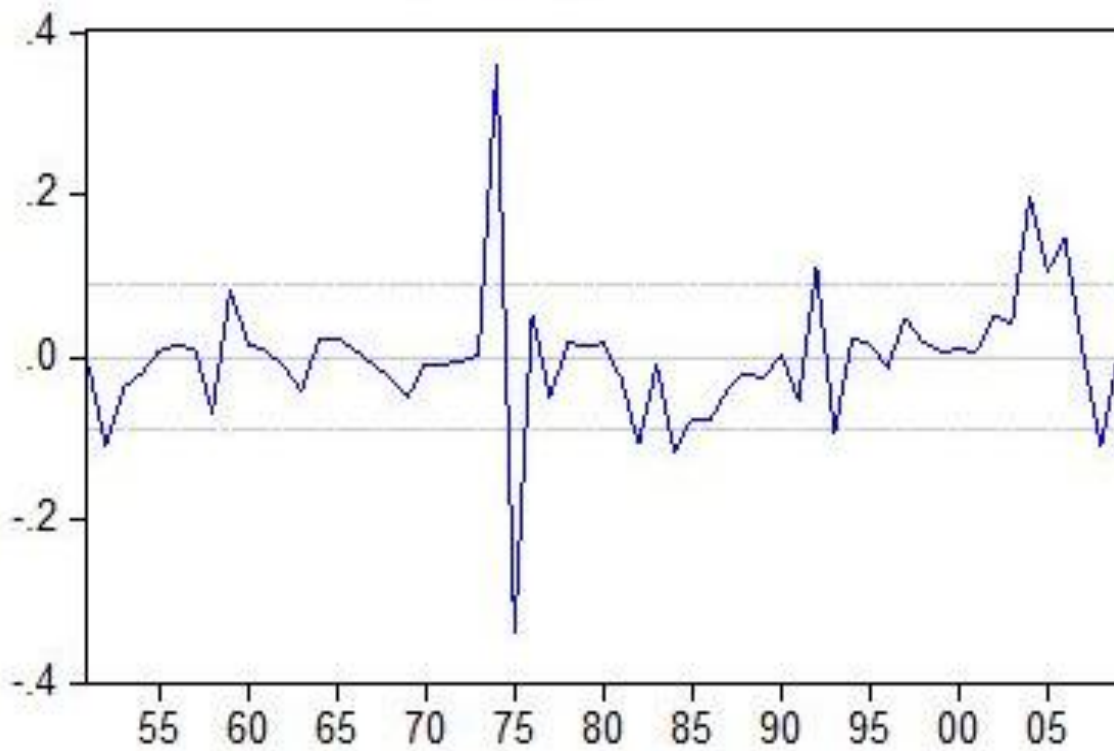


Figure 3.5. Estimated Residuals for Y_t over Period 1950-2009

Note: $U_{2,t+1}$ is the estimated residual in

$$Y_{t+1} = Z_{t+1}Y_t + \zeta X_{t+1} - U_{2,t+1}Z_{t+1} \quad (3.5)$$

 Equation (3.5) is estimated with Two-stage GMM in Eview7.

reported in table 3.3. Figure 3.4 demonstrates recursively estimated coefficients for X_{t+1} , Z_{t+1} , and v_{t+1} over the period of 1950-2009, and figure 3.5 demonstrates estimated residuals for Y_{t+1} in the period of 1950-2009.

3.4.3.1. Forecast Error Decomposition for Y_{t+1}

By the definition of $\epsilon_{2,t+1}$ in equation (3.11)

$$\epsilon_{2,t+1} = \zeta \epsilon_{1,t+1} + Y_t \epsilon_{3,t+1} - U_{2,t+1} a_3 - U_{2,t+1} b_3 Z_t - U_{2,t+1} \epsilon_{3,t+1} \quad (3.11)$$

We have the forecast error term of Y_{t+1}

$$\begin{aligned}
FE_{t+1}(Y_{t+1}) &= \zeta\epsilon_{1,t+1} - (a_3 + b_3Z_t)\epsilon_{2,t+1} + Y_t\epsilon_{3,t+1} = \zeta\epsilon_{1,t+1} - (a_3 + \\
&\quad b_3Z_t)(\zeta\epsilon_{1,t+1} + Y_t\epsilon_{3,t+1} - U_{2,t+1}a_3 - U_{2,t+1}b_3Z_t - U_{2,t+1}\epsilon_{3,t+1}) + Y_t\epsilon_{3,t+1} \\
&= \zeta\epsilon_{1,t+1}(1 - a_3 - b_3Z_t) + (a_3 + b_3Z_t)^2 U_{2,t+1} + (1 - a_3 - b_3Z_t)Y_t\epsilon_{3,t+1} + \\
&\quad (a_3 + b_3Z_t) U_{2,t+1}\epsilon_{3,t+1} \tag{3.21}
\end{aligned}$$

As table 3.3 shows, the significance level of correlations between $\epsilon_{1,t+1}$ and $U_{2,t+1}$, and $U_{2,t+1}$ and $\epsilon_{3,t+1}$ is higher than 5% in the whole sample. Therefore, we assume $\epsilon_{1,t+1} \perp U_{2,t+1}$ and $U_{2,t+1} \perp \epsilon_{3,t+1}$ at significance level 5%.

$$\Rightarrow \rho_{12} = \rho_{23} = 0$$

$$\begin{aligned}
Var(FE_{t+1}(Y_{t+1})) &= [\zeta(1 - a_3 - b_3Z_t)]^2 \sigma_1^2 \\
&\quad + (a_3 + b_3Z_t)^4 \sigma_2^2 + [(1 - a_3 - b_3Z_t)Y_t]^2 \sigma_3^2 + (a_3 + b_3Z_t)^2 \sigma_2^2 \sigma_3^2 + \\
&\quad 2[\zeta(1 - a_3 - b_3Z_t)^2 Y_t] \rho_{13} \sigma_1 \sigma_3 \tag{3.22a}
\end{aligned}$$

$$\begin{aligned}
Var(FE_{t+2}(Y_{t+2})) &= \{[1 - a_3 - b_3Z_t]^2 + [b_1 + (a_3 + b_3Z_t) - (a_3 + b_3Z_t)^2]^2\} \zeta^2 \sigma_1^2 \\
&\quad + [(a_3 + b_3Z_t)^4 + (a_3 + b_3Z_t)^6] \sigma_2^2 + \{[1 - a_3 - b_3Z_t]^2 + [a_3 + b_3Z_t + \\
&\quad b_3 - (a_3 + b_3Z_t)^2]^2\} Y_t^2 \sigma_3^2 + [(a_3 + b_3Z_t)^2 + (a_3 + b_3Z_t)^4] \sigma_2^2 \sigma_3^2 + \\
&\quad 2\{(1 - a_3 - b_3Z_t)^2 + [b_1 + (a_3 + b_3Z_t) - (a_3 + b_3Z_t)^2][a_3 + b_3Z_t + \\
&\quad b_3 - (a_3 + b_3Z_t)^2]\} \zeta Y_t \rho_{13} \sigma_1 \sigma_3 \tag{3.22b}
\end{aligned}$$

$$\begin{aligned}
Var(FE_{t+3}(Y_{t+3})) &= \{[1 - a_3 - b_3Z_t]^2 + [b_1 + (a_3 + b_3Z_t) - (a_3 + b_3Z_t)^2]^2 + \\
&\quad [b_1^2 + (a_3 + b_3Z_t)(b_1 + a_3 + b_3Z_t) - (a_3 + b_3Z_t)^3]^2\} \zeta^2 \sigma_1^2 + [(a_3 + b_3Z_t)^4 + \\
&\quad (a_3 + b_3Z_t)^6 + (a_3 + b_3Z_t)^8] \sigma_2^2 + \{[1 - a_3 - b_3Z_t]^2 + [a_3 + b_3Z_t + \\
&\quad b_3 - (a_3 + b_3Z_t)^2]^2 + [(a_3 + b_3Z_t)(a_3 + b_3Z_t + b_3) + b_3^2 - (a_3 +
\end{aligned}$$

$$\begin{aligned}
& b_3 Z_t)^3]^2 \} Y_t^2 \sigma_3^2 + [(a_3 + b_3 Z_t)^2 + (a_3 + b_3 Z_t)^4 + (a_3 + b_3 Z_t)^6] \sigma_2^2 \sigma_3^2 + \\
& 2\{(1 - a_3 - b_3 Z_t)^2 + [b_1 + (a_3 + b_3 Z_t) - (a_3 + b_3 Z_t)^2][a_3 + b_3 Z_t + \\
& b_3 - (a_3 + b_3 Z_t)^2] + \\
& [b_1^2 + (a_3 + b_3 Z_t)(b_1 + a_3 + b_3 Z_t) - (a_3 + b_3 Z_t)^3][(a_3 + b_3 Z_t)(a_3 + b_3 Z_t + \\
& b_3) + b_3^2 - (a_3 + b_3 Z_t)^3]\} \zeta Y_t \rho_{13} \sigma_1 \sigma_3
\end{aligned} \tag{3.22c}$$

The deduction details could be found in Appendix F.

3.4.3.2. Forecast Error Variance Decomposition For Farmland Prices, p_{t+1}

By definition, we have $p_{t+1} = Y_{t+1} - v_{t+1}$, and $v_{t+1} = a_4 + b_4 v_t + \epsilon_{4,t+1}$.

According to table 3.3, the significance level of correlations between $\epsilon_{1,t+1}$ and $\epsilon_{4,t+1}$ is higher than 5% in the whole sample. Therefore, we assume $\epsilon_{1,t+1} \perp \epsilon_{4,t+1}$ at significance level 5%.

$$\Rightarrow \rho_{14} = 0$$

$$\epsilon_{4,t+1} \sim N(0, \sigma_4^2), \epsilon_{4,t+1}, \epsilon_{4,t+2}, \epsilon_{4,t+3} \text{ iid}$$

$$\Rightarrow \text{FE}_{t+1}(p_{t+1}) = \text{FE}_{t+1}(Y_{t+1}) - \epsilon_{4,t+1} \tag{3.23a}$$

$$\begin{aligned}
\text{Var}(\text{FE}_{t+1}(p_{t+1})) &= \text{Var}(\text{FE}_{t+1}(Y_{t+1})) + \sigma_4^2 + 2(a_3 + b_3 Z_t)^2 \rho_{24} \sigma_2 \sigma_4 + 2[(1 - a_3 - \\
& b_3 Z_t) Y_t] \rho_{34} \sigma_3 \sigma_4
\end{aligned} \tag{3.24a}$$

$$\Rightarrow \text{FE}_{t+2}(p_{t+2}) = \text{FE}_{t+2}(Y_{t+2}) - (\epsilon_{4,t+2} + b_4 \epsilon_{4,t+1}) \tag{3.23b}$$

$$\begin{aligned}
\text{Var}(\text{FE}_{t+2}(p_{t+2})) &= \text{Var}(\text{FE}_{t+2}(Y_{t+2})) + (1 + b_4^2) \sigma_4^2 + 2[(a_3 + b_3 Z_t)^2 + b_4(a_3 + \\
& b_3 Z_t)^3] \rho_{24} \sigma_2 \sigma_4 + 2\{(1 - a_3 - b_3 Z_t) + b_4[a_3 + b_3 Z_t + b_3 - (a_3 + \\
& b_3 Z_t)^2]\} Y_t \rho_{34} \sigma_3 \sigma_4
\end{aligned} \tag{3.24b}$$

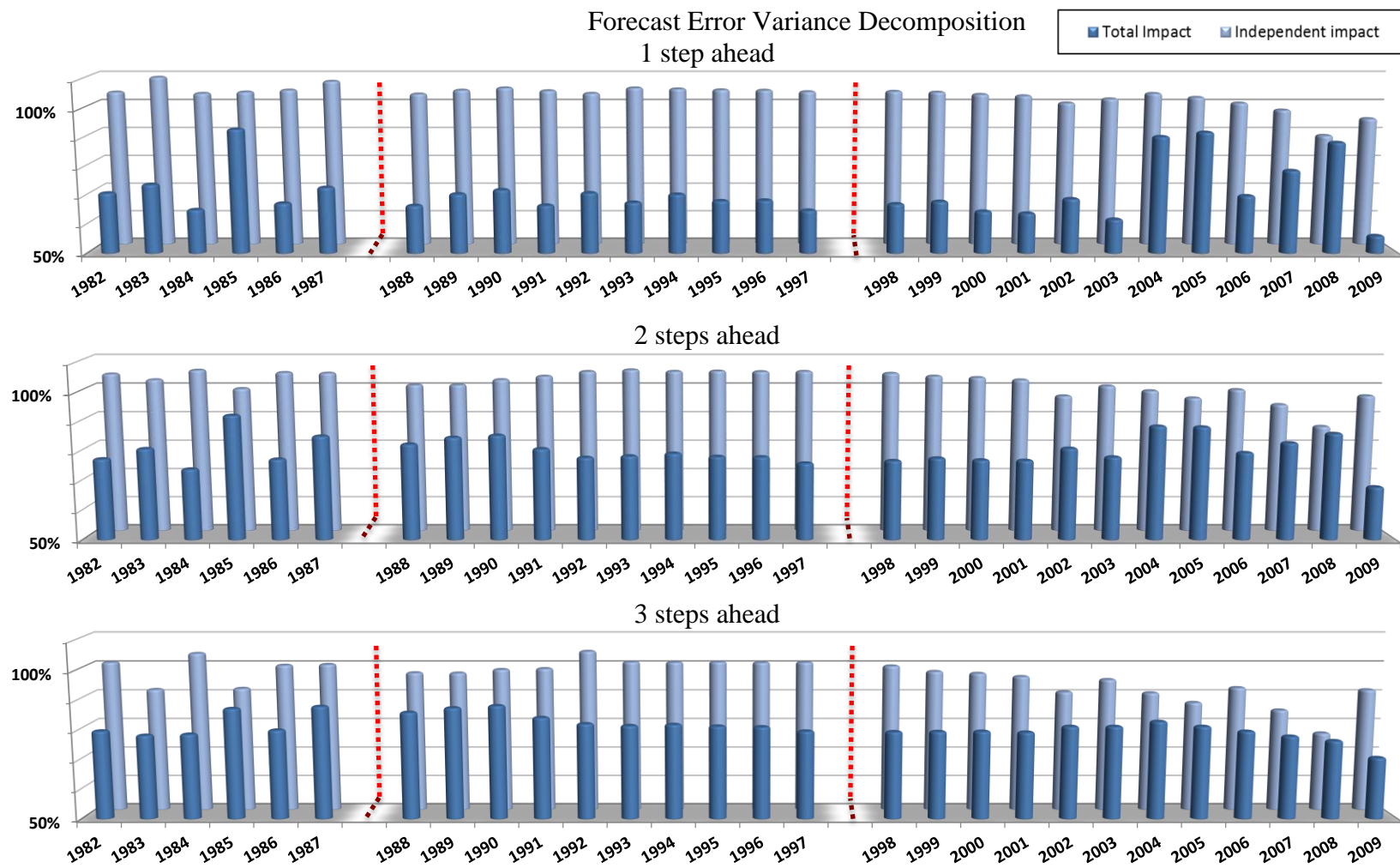


Figure 3.6. Percentages of Forecast Error Variance Decomposed into the Total and Independent Impacts of CAPM Error on Farmland Prices

$$\Rightarrow FE_{t+3}(p_{t+3}) = FE_{t+3}(Y_{t+3}) - (\epsilon_{4,t+3} + b_4\epsilon_{4,t+2} + b_4^2\epsilon_{4,t+1}) \quad (3.23c)$$

$$\begin{aligned} Var(FE_{t+3}(p_{t+3})) = Var(FE_{t+3}(Y_{t+3})) + b_4^4\sigma_4^2 + 2[(a_3 + b_3Z_t)^2 + b_4(a_3 + \\ b_3Z_t)^3 + b_4^2(a_3 + b_3Z_t)^4]\rho_{24}\sigma_2\sigma_4 + 2\{(1 - a_3 - b_3Z_t) + b_4[a_3 + b_3Z_t + \\ b_3 - (a_3 + b_3Z_t)^2] + b_4^2[(a_3 + b_3Z_t)(a_3 + b_3Z_t + b_3) + b_3^2 - (a_3 + \\ b_3Z_t)^3]\}Y_t\rho_{34}\sigma_3\sigma_4 \end{aligned} \quad (3.24c)$$

3.4.3.3. The Short-Run Forecast Variance Decomposition

When we substitute the values of data and coefficients listed in table 3.3 and 3.4 into equation (3.24a), the variance of forecast errors for p_{t+1} deducted in 3.2, we can calculate the percentage that specific error term(s) are of the total variance, or the impact of a time series on the forecast errors of farmland in the short run. This allows us to study the value of information carried in CAPM model.

First, as we have discussed in Section II, the prediction matrix for Y_{t+1} is nonlinear in X_t , Y_t , and Z_t . The variance of forecast errors of Y_{t+1} contains both the independent impacts of Y_t denoted in error terms of Y_t with non-stochastic data and coefficients, and the joint impacts of Y_t and other time series denoted in error terms of Y_t and Z_t with non-stochastic data and coefficients. Second, since we do not orthogonalize data before impulse response analysis, the variance of forecast errors of p_{t+1} contains covariance terms denoted in error terms of Y_t and v_t with non-stochastic data, coefficients, and correlation. Therefore, figure 3.6 shows 2 percentages of the CAPM errors over the variance of forecast errors of p_{t+1} : percentage of independent impact and percentage of total impact with both independent and joint impacts.

Figure 3.6, 1 step ahead FEVD, shows that in both the busting and booming stages, the total impacts of CAPM errors are bigger than those in the stable stage, and the total impacts have more variation in the booming stage than in the busting stage. This result is consistent with the general findings on the higher volatility of bigger amount of information. For instant, Zarnowitz and Lambros (1987) found that expectations of higher inflation generate greater uncertainty about inflation. Kagel and Levin (1986) also found that public information about the value of the item increases seller revenue in the absence of a winner's curse, but produces the contrary result in its presence, which means higher price variation in general.

3.4.3.4. The Middle-Run and Long-Run Forecast Variance Decomposition with Chain Rule

When we substitute the values of data and coefficients into equation (3.24b), the variance of forecast errors for p_{t+2} as in 3.2, we can calculate the impacts of CAPM errors on the forecast errors of farmland in the middle run. Figure 3.6, 2 steps ahead FEVD, also shows that in both the busting and booming stages, the total impacts of CAPM errors are bigger than those in the stable stage, and the total impact has more variations in the booming stage than in the busting stage over a middle term. As defined in Section III 2.2, “We define the stage when the farmland prices are persistently higher than the implication of the present value model as a booming stage, persistently lower as a busting stage, and consistent as a stable stage.”

When we substitute the values of data and coefficients into equation (3.24c), the variance of forecast errors for p_{t+3} deducted in 3.2, we can calculate the impacts of CAPM errors on the forecast errors of farmland in the long run. Figure 3.6, 3 steps ahead FEVD, shows that the total impacts of CAPM errors are bigger in the busting stage than those in the stable stage, and bigger than those in the booming stage.

The above findings are consistent with existing literature on the absorption behavior of economic information: information is not completely absorbed in the short run, but it is almost futile in the long run. For instance, Piotroski (2000) found that only one-sixth of the annual return difference between ex ante strong and weak firms is earned over the four three-day periods surrounding their quarterly earnings announcements. The market does not incorporate financial information into prices in a timely manner. Campbell et al (2003) found that in a stock market the economic consequences of information disclosure are trivial over the long run.

3.4.3.5. Further Discussion

Since traditional FEVD in orthogonalized linear models only contains direct impacts that are all positive, every decomposed portion is less than the summation of FEVD, 1. However, general FEVD with un-orthogonalized nonlinear models like the one in this chapter, may result in decompositions bigger than 1, as observed in figure 3.6. Next we discuss several relevant aspects of the range of decompositions in general models.

3.4.3.5.1. Explanation for (Percentage of Independent Impact of CAPM Error) Greater Than 1

To illustrate why the forecast error variance decomposition for p_{t+1} could be bigger than 1, we first write out the forecast error variance of p_{t+1} . As table 3.3 shows, $\epsilon_{1,t+1} \perp U_{2,t+1}$ and $U_{2,t+1} \perp \epsilon_{3,t+1}$ at significance level 5%,

$$\Rightarrow \rho_{12} = \rho_{23} = 0.$$

$$\begin{aligned} Var(\text{FE}_{t+1}(Y_{t+1})) &= [\zeta(1 - a_3 - b_3 Z_t)]^2 \sigma_1^2 \\ &\quad + (a_3 + b_3 Z_t)^4 \sigma_2^2 + [(1 - a_3 - b_3 Z_t)Y_t]^2 \sigma_3^2 + (a_3 + b_3 Z_t)^2 \sigma_2^2 \sigma_3^2 + \\ &\quad 2[\zeta(1 - a_3 - b_3 Z_t)^2 Y_t] \rho_{13} \sigma_1 \sigma_3 \end{aligned}$$

Also, we have $\epsilon_{1,t+1} \perp \epsilon_{4,t+1}$ at significance level 5%,

$$\Rightarrow \rho_{14} = 0$$

$$\begin{aligned} Var(\text{FE}_{t+1}(p_{t+1})) &= Var(\text{FE}_{t+1}(Y_{t+1})) + \sigma_4^2 + 2(a_3 + b_3 Z_t)^2 \rho_{24} \sigma_2 \sigma_4 \\ &\quad + 2[(1 - a_3 - b_3 Z_t)Y_t] \rho_{34} \sigma_3 \sigma_4 \\ &= [\zeta(1 - a_3 - b_3 Z_t)]^2 \sigma_1^2 + (a_3 + b_3 Z_t)^4 \sigma_2^2 + [(1 - a_3 - b_3 Z_t)Y_t]^2 \sigma_3^2 \\ &\quad + (a_3 + b_3 Z_t)^2 \sigma_2^2 \sigma_3^2 + 2[\zeta(1 - a_3 - b_3 Z_t)^2 Y_t] \rho_{13} \sigma_1 \sigma_3 + \sigma_4^2 + 2(a_3 + \\ &\quad b_3 Z_t)^2 \rho_{24} \sigma_2 \sigma_4 + 2[(1 - a_3 - b_3 Z_t)Y_t] \rho_{34} \sigma_3 \sigma_4 \end{aligned}$$

Percentage of independent impact of CAPM error

$$= (a_3 + b_3 Z_t)^4 \sigma_2^2 / Var(\text{FE}_{t+1}(p_{t+1}))$$

Percentage of total impact with both independent and joint impacts of CAPM error

$$\begin{aligned} &= [(a_3 + b_3 Z_t)^4 \sigma_2^2 + (a_3 + b_3 Z_t)^2 \sigma_2^2 \sigma_3^2 + 2(a_3 + b_3 Z_t)^2 \rho_{24} \sigma_2 \sigma_4] / \\ &Var(\text{FE}_{t+1}(p_{t+1})) \end{aligned}$$

As we can see in table 3.3, $\rho_{13} > 0$, $\rho_{24} < 0$, and $\rho_{34} < 0$, therefore, it is possible that

$$(a_3 + b_3 Z_t)^4 \sigma_2^2 > \text{Var}(\text{FE}_{t+1}(p_{t+1}))$$

\Rightarrow Percentage of independent impact > 1

By the same token, the forecast error variance decomposition for p_{t+2} and p_{t+3} could also be bigger than 1.

3.4.3.5.2. Economic Implications for (Percentage of Independent Impact of CAPM Error) Greater Than 1

Since the error term in the random walk of transaction cost is negatively correlated to the error term in the CAPM ($\rho_{24} < 0$) and adjusted growth rate of disposable income ($\rho_{34} < 0$), the error terms of forecast under QRE for farmland prices ($\text{Var}(\text{FE}_{t+1}(p_{t+1}))$) could be smaller than those under RE ($(a_3 + b_3 Z_t)^4 \sigma_2^2$).

3.4.3.5.3. Summation of (Percentage of Impact of Error Terms) Equals 1

It is straight forward to prove that for all kinds of forecast error variance decompositions, with or without orthogonalization:

$$\text{Sum (Percentage of joint impacts)} + \text{Sum (Percentage of independent impacts)} = 1 \quad (3.25)$$

In linear models, terms like $(a_3 + b_3 Z_t)^2 \sigma_2^2 \sigma_3^2$ do not exist, and orthogonalization makes correlations like $\rho_{24} = 0$, causing terms like $2(a_3 + b_3 Z_t)^2 \rho_{24} \sigma_2 \sigma_4 = 0$. Therefore, Percentage of joint impacts = 0, and equation (3.25) reduces to

$$\text{Sum (Percentage of independent impacts)} = 1 \quad (3.26)$$

3.4.3.5.4. Attenuating Joint Impacts

As we can see, there is a trend that the joint impacts at horizon 1 are larger in absolute value, as a decomposed ratio, than at horizon 2 and 3. The explanation is straightforward.

Since we use the chain-rule and assume iid for inter-temporal error terms, part of the joint impacts in horizon 1, some correlation type of joint impacts, become 0 in horizon 2. Therefore the decomposed ratio of all joint impacts becomes smaller in horizon 2 in absolute value than in horizon 1 (given that all correlations included are of the same sign as the total impacts). By the same token, the decomposed ratio of all joint impacts becomes smaller in horizon 3 in absolute value than in horizon 2.

The story behind this is that the joint impacts from non-linearity are persistent, while those from un-orthogonalization fade away in time. In an infinite horizon, the decomposed ratio of the un-orthogonalized joint impacts will approach that of the orthogonalized ones over time.

3.5. Conclusion

In this essay we follow the agricultural economics literature and refer to the three stages of land prices as “boom”, “bust”, and “stable” (Schmitz 1995). Further research relating these notions to the mathematics of the characteristic equation (Box and Jenkins 1976) is certainly worthwhile.

The moving average representation shows that in the short run, the CAPM portion of the variance of QRE forecast errors are significantly higher in a boom or bust stage than in a stable stage. This means that the market values the economic information from the CAPM more in an unstable stage than in a stable stage. Since CAPM explains different levels of the uncertainty in the different stages of land valuation (i.e., boom, bust, and stable), the market is reacting differently to economic information over cycles. Thus static time invariant representations of land valuation models are not capturing the entire picture of land valuation.

Further, the higher portion of the CAPM variance disappears quickly in the long run forecasts in a boom stage with chain rule, which could be explained by the expected market adaptation for farmland prices. The fact that discrepancies between information utilization in the stable versus non-stable stages diminishes over time – suggests that markets are adapting to this information over a longer time horizon.

In conclusion, the farmland market absorbs economic information in a discriminative manner according to the stability of the market, and the market (and actors therein) responses to new information gradually as suggested by the theory. This discriminative market behavior in the absorption of CAPM information helps to explain the overpricing of farmland, but this explanation works primarily in the short run.

Additional work contrasting FEVD from the nonlinear model with more structural linear model FEVD would be worth consideration. Here we find several decompositions exceeding 100%, due to our inability to break the movement of two correlated variables. Further research explaining this result would be beneficial.

Additional work could also be done with the orthogonalization of the error terms among different time series. Finally, the long run analysis could be more meaningful with high frequency data, such as futures, stocks, and foreign exchanges.

CHAPTER IV

THE DUAL EFFECTS OF CLIMATE CHANGE AND DIRECT GOVERNMENT PAYMENTS ON FARMLAND VALUATION

In this chapter, we study the dual effects of climate change and direct government payments on farmland valuation, through their effects on revenues and interactions with risk aversion. We adopt the DLPM developed in Chapter II to a panel data set for U.S. farmland valuation at state level, during the period of 1960-2007. This study denotes heterogeneity of risk aversion across different states and time periods with a semi-parametric form. The parameter α , reflecting Risk Aversion Coefficient (RAC), is defined as a smooth coefficient function of direct government payments and climate change, to enhance the robustness of the panel model against risk aversion misspecifications.

4.1. Background

Climate change and direct government payments can affect farmland prices via two paths. First, both climate change and direct government payments have impacts on crop revenues, which in turn determine net income and are capitalized into land values. Second, both climate change and direct government payments affect risk aversion of the farmers by changing crop revenues and farm wealth levels, and the risk aversion of farmers affects land values through discounting factors. It is well documented that farm

wealth levels are related to relative-risk-aversion-coefficient (Pratt 1964; Arrow 1965), and risk aversion affects land prices (Just and Miranowski 1993).

A dynamic land pricing model (DLPM) is a CAPM extension, which discounts future revenues into a present value of the asset. Traditional DLPMs include farm revenues as data in their model and estimate risk aversion as a fixed parameter (Chavas and Thomas 1999). For instance, if a piece of farmland is subject to better weather conditions or receives higher amounts of government payments, the crop revenues of this farm will be higher. A traditional DLPM tells us that this farmland would be worth more on the real estate market due to its higher future revenues. Obviously, traditional DLPMs capture the revenue effects of climate change and direct government payments on farmland valuation. However, the traditional approach estimates risk aversion as a fixed parameter, which omits the influence of climate change and direct government payments on the degree of risk aversion. Therefore, traditional DLPMs are vulnerable to risk aversion misspecifications in the discounting process of CAPM.

The objective of this essay is to investigate the dual effects of direct government payments and climate change on farmland values, using a smooth coefficient semi-parametric panel data model. This essay adopts a model that overcomes the limitation of fixed parameter for risk aversion by allowing the risk aversion to change over time and space. A semi-parametric estimator, smooth coefficient estimation, is used to estimate the risk aversion in DLPMs. DLPMs are extended to capture the dual effects of climate change and direct government payments on farmland prices, through both the influence on future revenues and discounting process. Specifically, we extend the general DLPM

developed in Chapter II to deal with climate change and government payments in a panel model.

Although most present value models are rejected by empirical data (Falk 1991; Schmitz 1995), we believe that risk aversion misspecification is a missing key to the farmland valuation puzzle in those models. Our model will take consideration of the variation of risk aversion, and estimate DLPM under the supposition that the risk aversion changes geographically and temporally (Gómez-Limón, Arriaza, and Riesgo 2002). We expect our empirical results to be consistent with the major findings of the present value capitalization formula, and provide evidence for the omitted risk aversion effect of climate change and government payments on farmland valuation (Moss and Katchova 2005).

4.1.1. Climate Change and Farmland Values

A number of studies have examined the effect of climate change on land values. Principal approaches have involved the Ricardian approach and spatial correlations.

4.1.1.1. Ricardian Approach

The Ricardian approach to examine climate change effects on land values is straight forward. The unit farmland rental rates across different locations are regressed on climate data in those locations with US county data. Mendelsohn, Nordhaus, and Shaw (1994) found that higher temperatures reduce farm values, while more precipitation increases farm values, in all seasons except autumn. They also studied the

relationship between climate and farm revenues. The climate data used by Mendelsohn, Nordhaus, and Shaw includes four season temperatures in degrees Fahrenheit, precipitation in inches per month, and their squares.

4.1.1.2. Spatial Correlation

Schlenker, Hanemann, and Fisher (2006) extended the Ricardian approach to account for spatial correlation across regions. Schlenker, Hanemann, and Fisher (2006) used logged farmland values as the dependent variable, and a climate variable “degree days” which is a nonlinear transformation of the climatic variables in the growing season. The climate data they used include degree days, its square and square root, as well as precipitation and its square. Further, Schlenker, Hanemann, and Fisher (2006) used their spatial estimates for predictions, and found a significant effect of climate change on farmland values.

4.1.2. Government Payments and Farmland Prices

Besides climate itself, government policies are also determinants of farmland valuation. However, there are no conclusive findings on the effect of government payments on farmland prices (Moss and Katchova 2005). For instance, Chavas and Shumway (1982) found that an increase of 10% in corn prices would raise the expected land prices in Iowa by 2.5% ~ 4.2%. But Moss, Shonkwiler, and Reynolds (1989) found that government payments had little effect on farmland values in the long run and a decreasing effect in the short run.

4.1.2.1. The 2008 Farm Act

“The Food, Conservation, and Energy Act of 2008” (the 2008 Farm Bill) was enacted into law in June 2008. The 2008 Farm Bill governs the substance of Federal agriculture and related programs for 5 years: June 2008- May 2013. The 15 titles of the 2008 Farm Bill include administrative and funding authorities for a wide range of programs. Figure 4.1 shows annual Government Payments of different programs to the farm sector during 1996~2008 (Young, Oliveira, and Claassen 2008). There are two kinds of programs that alter farmland revenues: commodity programs and conservation programs.

4.1.2.1.1. Commodity Programs

Commodity programs are intended to help farmers stabilize their incomes. Price and income supports are provided through core programs for grains, oilseeds, fiber, dairy, and sugar. The expenditures of commodity programs vary significantly over time, and they are heterogeneous in space. For instance, commodity programs are concentrated in major producing areas: highest in the Southeastern Coastal Plain, where cotton and peanuts are produced, and along the lower Mississippi River, where cotton and rice are grown.

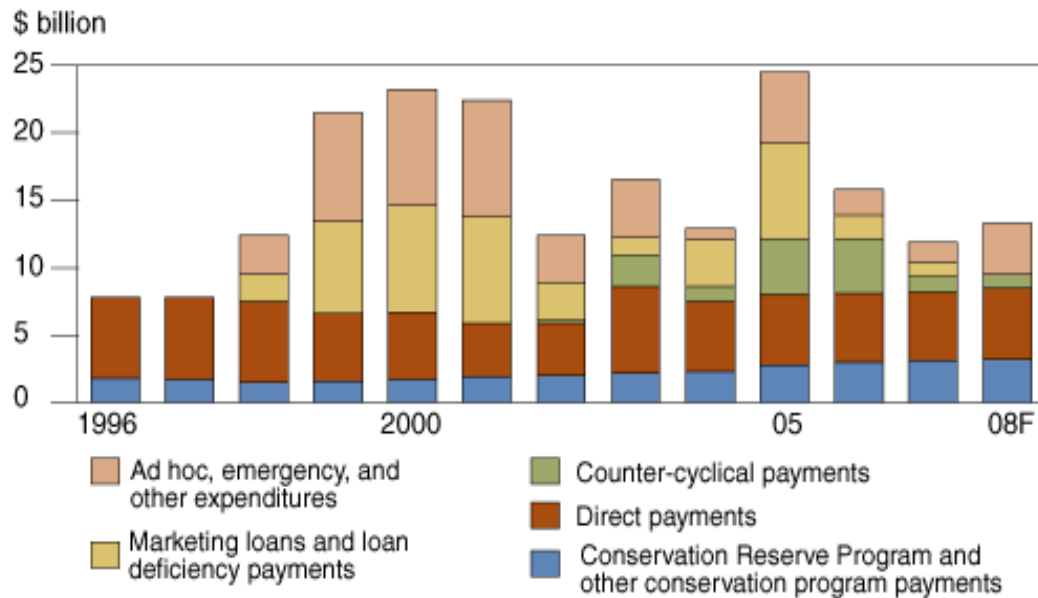


Figure 4.1. Government Payments of Different Programs during 1996~2008

Note: USDA data are cited as in Young, Oliveira, and Claassen 2008. 08F = Forecast for 2008.

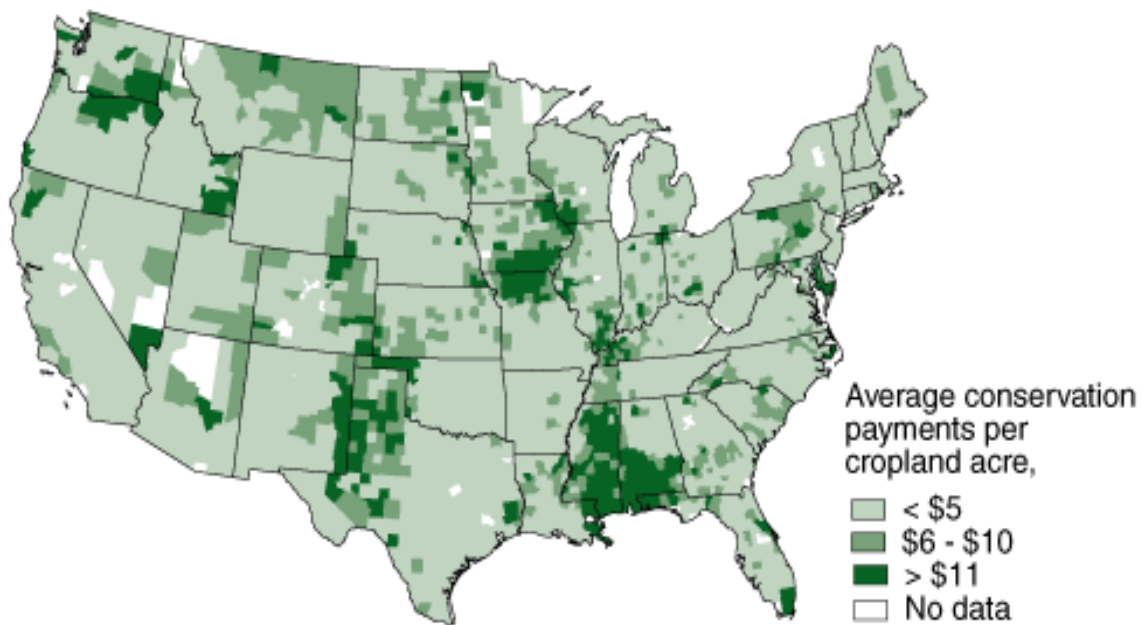


Figure 4.2. Conservation Payments Distribution across US during 2004-2007

Note: USDA data are cited as in Young, Oliveira, and Claassen 2008. Source: USDA, Economic Research Service using data from USDA, Farm Service Agency and USDA, National Agricultural Statistics Service, 2009

4.1.2.1.2. Conservation Programs

Conservation programs are intended to help farmers address environmental concerns. The two largest agri-environmental programs are the Conservation Reserve Program (CRP) and the Environmental Quality Incentives Program (EQIP). Wu, Ziberman, and Babcock (2001) studied the distributional impacts of conservation payments, and found that price feedback effects associated with negatively sloped output demand are important to the optimal design of targeting criteria.

The 2008 Farm Bill established the Conservation Stewardship Program (CSP), to replace the Conservation Security Program established under the 2002 Farm Bill. The 2008 Bill also increases funding for the EQIP and CSP to better address environmental needs for land in production. But the 2008 Bill reduces expenditures on the CRP for land retirement. These changes will shift spending from reservation areas to primary production regions such as the Corn Belt and Delta States (Young, Oliveira, and Claassen 2008). Figure 4.2 shows the conservation payments distribution across US during 2004-2007.

4.1.2.1.3. The 2008 Farm Bill and Farmland Pricing

Now, we explore why the 2008 Farm Bill might impact farmland pricing. The 2008 Farm Bill introduces Average Crop Revenue Election (ACRE) program payments, and offers farmers the choice to remain in 2002 Direct and Counter-Cyclical Programs (DCP) or to enroll in a new ACRE program. The ACRE program protects farmers against revenue losses due to falling prices and low yields. By enrolling in ACRE,

farmers renounce 20 percent of their certain direct payment for the potential of a larger ACRE payment in a bad year. For farmers enrolling in ACRE, larger government payments would be expected when low prices or reduced yields cut farm revenues.

The decision to enroll in either DCP or ACRE will affect farm profits and in turn farmland values. The enrollment in farm programs varies across the nation. First, farmers producing cotton, peanut, and rice are less likely to enroll in ACRE, because they would forego high payments provided under the DCP program. Second, farmers producing corn, soybean, and wheat are more likely to enroll in ACRE, because current market prices are well above the target prices set in the DCP program. Third, farmers located in states with more volatile yields, such as wheat farmers in Oklahoma, are the most likely to enroll in ACRE (Briggeman and Campiche 2010). Therefore, the enacting of the 2008 Farm Bill has a heterogeneous impact on farmland values through altered farmland revenues.

4.1.2.2. Direct Government Payments under the Act

Under the provisions of the 2008 Farm Bill, direct government payments include payments for commodity programs such as direct payments (DPs), counter-cyclical payments (CCPs), as well as marketing loan benefits such as marketing loan gains (MLGs), loan deficiency payments (LDPs), and certificate gains. Also included in direct government payments are emergency and disaster payments, tobacco transition payments, conservation program payments, and ACRE program payments.

4.1.2.2.1. Direct Government Payments under the 2008 Farm Bill

Direct payments have accounted for a significant portion of farm program payments since 2003. According to USDA's annual Agricultural Resource Management Survey (ARMS), 37 percent of all farms were eligible to receive government payments in calendar year 2009. The average payment was \$11,549, accounting for 5.5 percent of gross farm level cash income, or 23.6 percent of net farm level cash income. Receipt of direct government payments is unevenly distributed, with most going to large farms. The largest 12.4 percent of eligible farms received 62.2 percent of all government payments in 2009 (USDA Economic Research Service, November 07, 2012). This information is found at: <http://www.ers.usda.gov/topics/farm-economy/farm-commodity-policy/government-payments-the-farm-sector.aspx>.

4.1.2.2.2. Direct government payments and crop revenue

Figure 4.3 shows the percentage of direct payments relative to crop revenue, by county, 2004-2008. As we can see in figure 4.3, direct payments are highest relative to crop revenues in the Northern Plains, Southern Plains, Mountain, Delta, and Southeast regions. Ifft et al (2012) found that direct payments per farm tend to be the highest in the Delta and Southeast regions.

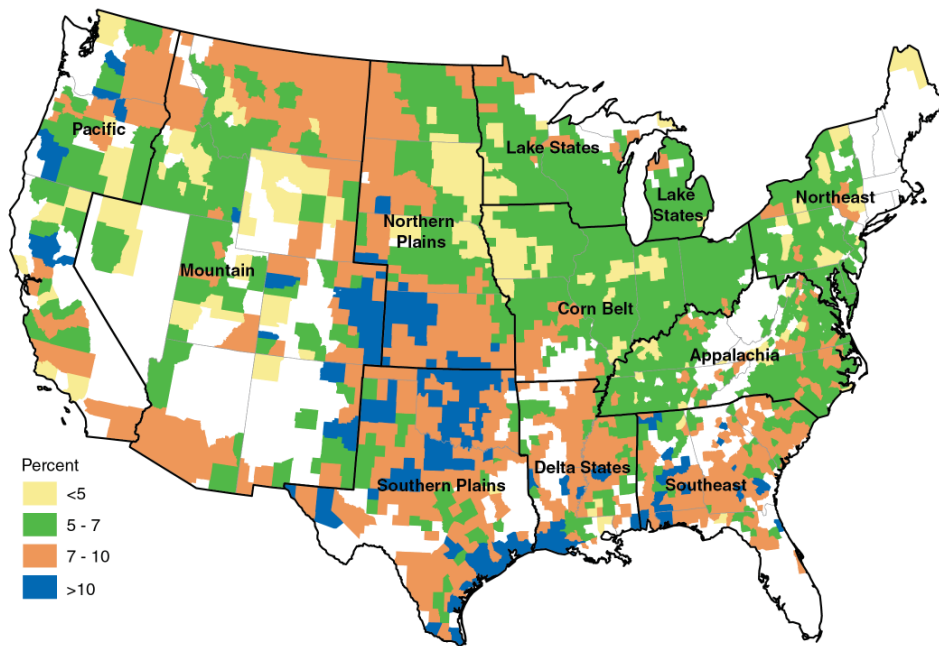


Figure 4.3. Direct Payments as a Percent of DP Program Crop Revenue, by County, 2004-2008

Note: USDA data are cited as in Ifft et al 2012. Source: USDA, Economic Research Service calculations based on National Agricultural Statistics Service Quick Stats data; Economic Research Service and National Agricultural Statistics Service 2007 Census of Agriculture data; and USDA, Farm Service Agency Direct and Counter-Cyclical Payment Program farm crop, contract and producer payment data. Blank areas identify counties with no direct payments, or fewer than 2,000 base acres or fewer than 5,000 cropland acres in 2007 Census of Agriculture.

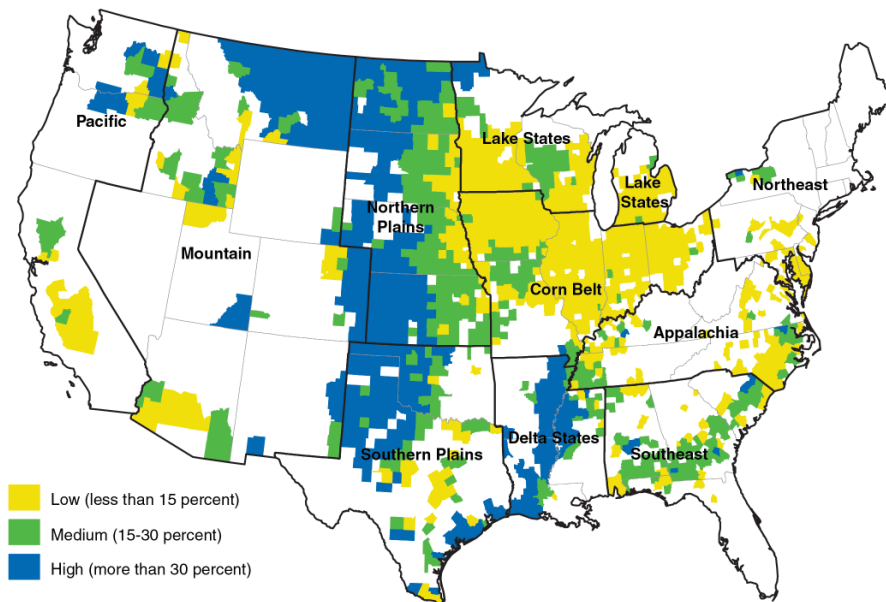


Figure 4.4. Maximum Impact of Capitalized Direct Payments on Cropland Values per Acre, 2004-2008

Note: USDA data are cited as in Ifft et al 2012. Source: USDA, Economic Research Service calculations based on USDA, National Agricultural Statistics Service June Area Survey data and the USDA, Farm Service Agency base acre and Producer Payment Reporting System Payment files.

Cropland values are an average of both irrigated and non-irrigated cropland values from the USDA, National Agricultural Statistics Service June Area Survey. Blank areas identify counties with no direct payments, insufficient observations for disclosure, or fewer than 2,000 base acres per county. Counties where base acres account for less than a third of cropland acres were excluded, as average cropland values in such counties would be less representative of farms with base acres.

4.1.2.2.3. Direct Government Payments and Farmland Values

First, direct government payments have a significant impact on farmland values. Goodwin, Mishra, and Ortalo-Magné (2003) looked at the effect of payments on land values and found that a \$1-per-acre increase in production flexibility contract (PFC) payments was associated with a \$5-per-acre increase in farmland prices. Latruffe and Le Mouél (2009) reviewed a group of studies on US farmland prices, and found that 12% ~40% of the farmland prices were attributable to government payments.

Second, direct government payments impact farmland values in a heterogeneous pattern. Ifft et al (2012) studied the relationship between cropland values and expected earnings from future direct payments. They calculated the ratio of “capitalized direct payments” to cropland values as an estimate of the maximum potential contribution of direct payments to land values. Figure 4.4 exhibits this maximum impact of capitalized direct payments on cropland values per acre during 2004-2008. As we can see in figure 4.4, the estimated maximum contribution of direct payments to cropland values varies significantly by region. In the Corn Belt and Lake States, estimated ratios of capitalized direct payments to per-acre cropland values were relatively low (less than 15 percent). In contrast, estimated ratios in the Northern and Southern Plains, as well as part of the Delta States and the Mountain region, were relatively high (more than 30 percent). Nickerson et al (2012) also found that the correlation between government payments and cropland values varies regionally.

4.1.3. Semi-Parametric Approach and Curse of Dimensionality

We adopt a semi-parametric method to estimate our empirical model: to estimate the relative risk aversion coefficient with a non-parametric form of Smooth Coefficient Estimation (Li et al 2002, Li and Racine 2007a), and to estimate other coefficients as parameters in a Seemingly Unrelated Regression (Henderson et al 2010).

Hayfield and Racine (2007 and 2008) and Racine (2009) demonstrated that the performance of semi-parametric models in “in-sample fit” lies in between that of the misspecified parametric models and that of the fully nonparametric models. They also note that the nonparametric approach relaxes the usual assumptions of parameters, and allows us to uncover structures in the data that might be missed otherwise. Therefore fully nonparametric models provide more flexibility.

However, many nonparametric methods are affected by the so-called “curse of dimensionality”, caused by the sparsity of data in high-dimensional spaces. As the dimension of the regressor vector increases, the sparseness of data in high dimensional model causes the variances of the estimates to increase and they ultimately become unacceptably large under fully nonparametric methods (Geenens 2011). Thus in order to allow the risk aversion to shift with climate but still get low coefficient estimate variances in our model, we use a semi-parametric method.

The remainder of the essay is organized as follows. Section II describes the model. Section III details the construction of data and estimation procedures. Section IV illustrates the empirical results. Section V summarizes and concludes the essay.

4.2. The Model

We adopt the same model set up as that in Chapter II, with a Recursive Utility form (Koopmans 1960):

$$U_t = [(1 - \beta)y_t^\rho + \beta M_t^\rho]^{\frac{1}{\rho}} \quad (2.3)$$

where

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

The model is specified in terms of the First Order Conditions of the Dynamic Land Pricing Model:

The marginal utility of the current sacrifice = The marginal utility of the future gain

As discussed in Chapter 2, the three equations stand for the equilibrium between consumption and investment, cash, and farmland respectively.

$$\beta' E_t [(y_t/y_{t+1})^{1-\rho} (q_t/q_{t+1}) \lambda R_{t+1}] = 1 \quad (2.15a)$$

$$\beta' E_t [(y_t/y_{t+1})^{1-\rho} (q_t/q_{t+1}) (1 + r_{t+1})] = 1 \quad (2.15b)$$

$$\beta' E_t [(y_t/y_{t+1})^{1-\rho} (q_t/q_{t+1}) (\zeta \frac{\pi_{t+1}}{a_{j,t}} + (p_{j,t+1} + v_{j,t+1}))] = (p_{j,t} + v_{j,t}) \quad (2.15c)$$

where

$$\beta' = \frac{2-\alpha/\rho}{(\bar{r}+1)}$$

or

$$(2 - \alpha/\rho) (y_t/y_{t+1})^{1-\rho} (q_t/q_{t+1}) \lambda R_{t+1} / (\bar{r} + 1) - 1 = u_{0t} \quad (4.1a)$$

$$(2 - \alpha/\rho) (y_t/y_{t+1})^{1-\rho} (q_t/q_{t+1}) (1 + r_{t+1}) / (\bar{r} + 1) - 1 = u_{1t} \quad (4.1b)$$

$$(2 - \alpha/\rho) (y_t/y_{t+1})^{1-\rho} (q_t/q_{t+1}) (\zeta \frac{\pi_{t+1}}{a_t} + (p_{t+1} + v_{t+1})) / (\bar{r} + 1) - (p_t + v_t) = u_{2t} \quad (4.1c)$$

With most parameters and variables defined identically to those in Chapter II, there are 2 substantial differences between the current model and that in Chapter II:

- Instead of a time series model, we will use a panel data model to study the climate change and government payment's effects on farmland prices for different states in different years. Many data variables have two subscripts: time and U.S. state in this Chapter.
- We treat α , defined as in equation (2.3) as a smooth coefficient, rather than a parameter, and it is expressed in a nonparametric form of variables Z_{it} . As we have discussed in Section I. 3, the nonparametric approach will overcome the risk aversion misspecification problem in the panel model.

The current model is rewritten as follows.

$$(2 - \alpha/\rho) (y_{i,t}/y_{i,t+1})^{1-\rho} (q_{i,t}/q_{i,t+1}) \lambda R_{i,t+1}/(\bar{r}_i + 1) - 1 = u_{0it} \quad (4.2a)$$

$$(2 - \alpha/\rho) (y_{i,t}/y_{i,t+1})^{1-\rho} (q_{i,t}/q_{i,t+1}) (1 + r_{i,t+1})/(\bar{r}_i + 1) - 1 = u_{1t} \quad (4.2b)$$

$$(2 - \alpha/\rho) (y_{i,t}/y_{i,t+1})^{1-\rho} (q_{i,t}/q_{i,t+1}) (\zeta \frac{\pi_{i,t+1}}{a_{i,t}} + (p_{i,t+1} + v_{i,t+1}))/(\bar{r}_i + 1) - (p_{i,t} + v_{i,t}) = u_{2it} \quad (4.2c)$$

where

$$\alpha = g(Z_{i,t}) \text{ and } Z_{i,t} = (Rain_{i,t} \ Temperature_{i,t} \ GP_{i,t})$$

Variables in the above equations (4.2a), (4.2b), and (4.2c) are defined as follows:

- q_{it} : Consumer Price Index(1982~1984:1) for state i period t
- y_{it} : disposable income of farm population for state i period t (\$trillion)
- R_{it} : gross rate of return on farm equity for state i period t

- A_{it} : farm wealth levels (equity) for state i period t (\$100million)
- r_{it} : Interest rate on U.S. treasury bills (%)for state i period t
- p_{it} : Farm land price for state i period t (\$1,000/acre)
- $\pi_{i,t+1}/a_{it}$: net farm income per acre (\$1000/acre)
- v_{it} : transaction costs of year t in farmland market for state i (\$1,000/acre)
- Q_{it} : land quantity for state i period t
- $Rain_{it}$: Precipitations in inches for state i period (annual data)
- $Temperature_{it}$:Average Annual Temperatures in °F for state i period t
- GP_{it} : Government Payments for state i period t

4.3. Data and Estimation

The above model is developed for a representative agent and we assume that all the functional forms hold in aggregated panel data. The data on land values are collected from the USDA website, <http://www.ers.usda.gov/data-products/farm-income-and-wealth-statistics.aspx>. Farmland prices, acres used in productions, farm gross income, and other variables are collected during the period of 1960~2008 at the US state level. The climatic data are collected from NOAA using the National Climatic Data Center at website, <http://www.ncdc.noaa.gov/oa/climate/research/cag3/cag3.html>.

4.3.1. Data

Figure 4.5 shows the annual average state level precipitation in inches for the 48 contiguous US States over the period of 1960-2007, figure 4.6 shows the annual average state level temperatures in degrees Fahrenheit for the US States, 1960-2007, and figure 4.7 shows the annual Government Payments in thousand dollars for the US States, 1960-2007. As we can see in figure 4.5-7, the variables, climate changes and Government Payments, have 3 important characteristics during the period of our research:

- Precipitation has higher volatility than does temperature, which indicates that precipitation may contain more information and act as a better explanatory variable than temperature.
- Annual average temperatures have a positive trend over time. This trend reflects climate change in the last 50 years in the US as discussed in Intergovernmental Panel on Climate Change (IPCC 2007).
- Government Payments increased between 1980 and 2007 with large year to year variability. It is apparent that government payments demonstrate two different patterns before and after 1980. This means that the distribution of government payments at low level may be significantly different from that at high level.

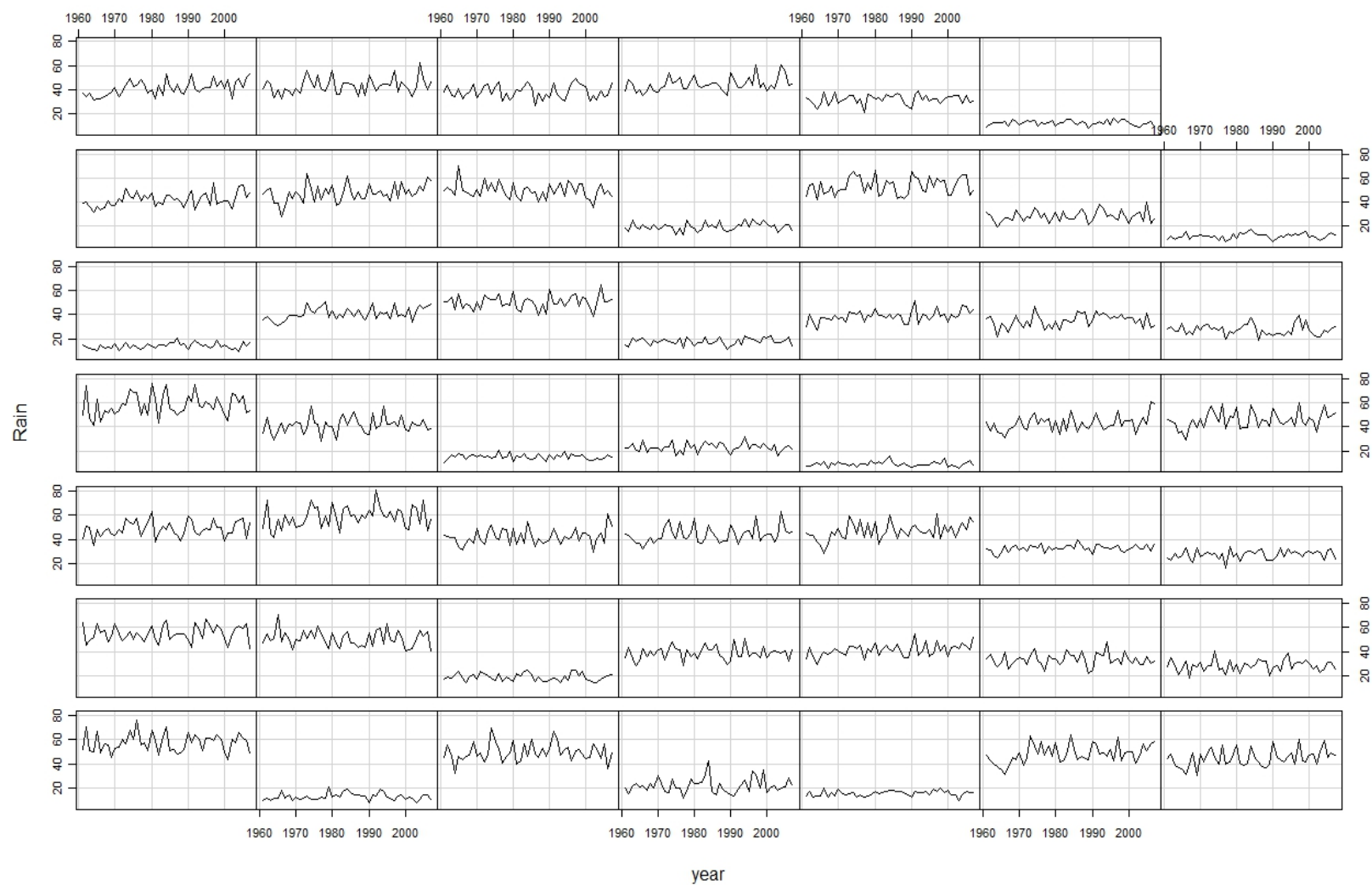


Figure 4.5. Annual Average Precipitations in Inches for US States (Except For Hawaii And Alaska),1960-2007.

Figure 4.5. Continued

Note: The states are listed alphabetically in rows starting with Alabama and going through Wyoming.

1	2	3	4	5	6	7
Vermont	Virginia	Washington	West Virginia	Wisconsin	Wyoming	
Pennsylvania	Rhode Island	South Carolina	South Dakota	Tennessee	Texas	Utah
New Mexico	New York	North Carolina	North Dakota	Ohio	Oklahoma	Oregon
Mississippi	Missouri	Montana	Nebraska	Nevada	New Hampshire	New Jersey
Kentucky	Louisiana	Maine	Maryland	Massachusetts	Michigan	Minnesota
Florida	Georgia	Idaho	Illinois	Indiana	Iowa	Kansas
Alabama	Arizona	Arkansas	California	Colorado	Connecticut	Delaware

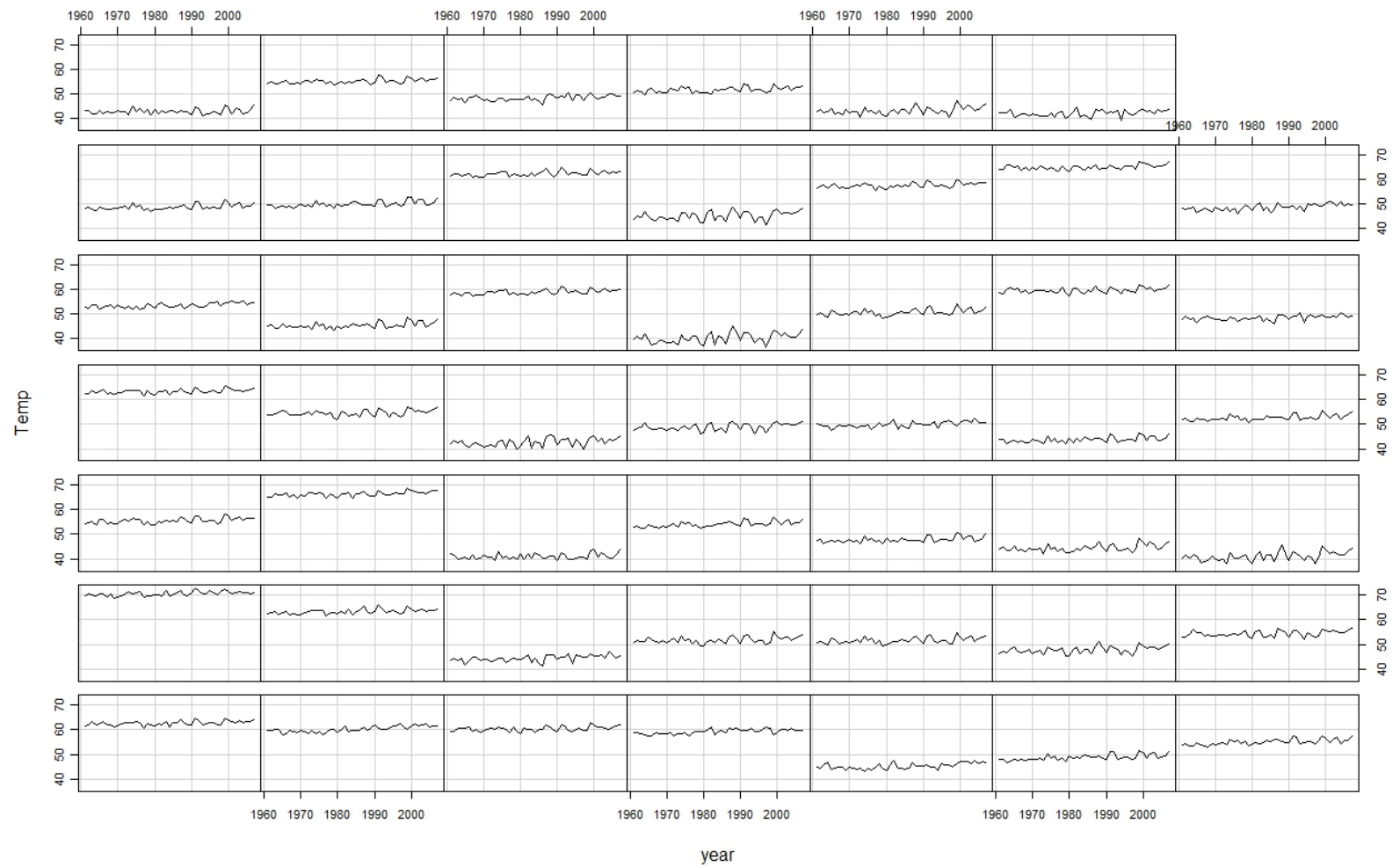


Figure 4.6. Annual average Temperatures in Degrees Fahrenheit for US States (except for Hawaii and Alaska), 1960-2007

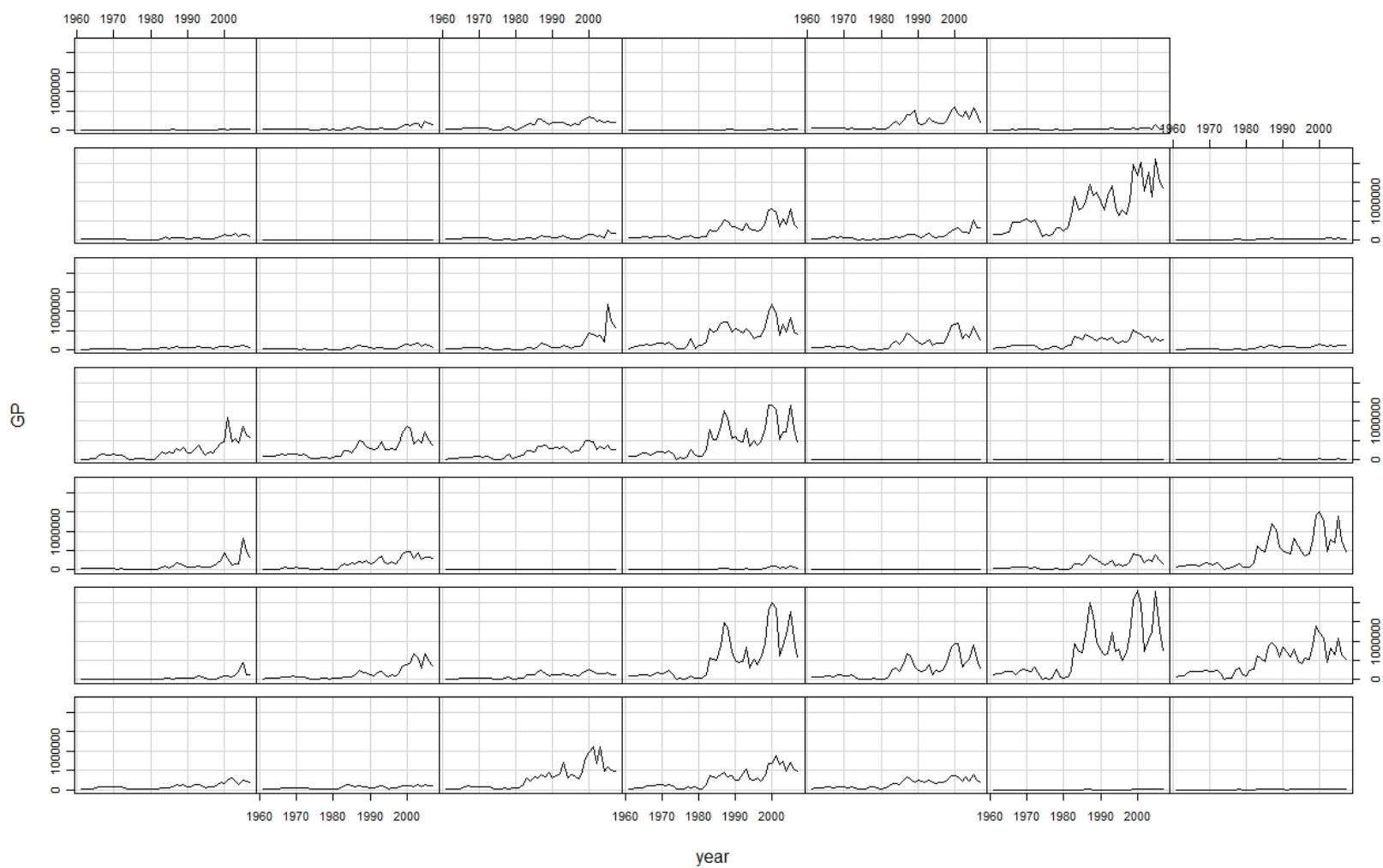


Figure 4.7. Annual Government Payments in Thousands of Dollars for US States (except for Hawaii and Alaska), 1960-2007

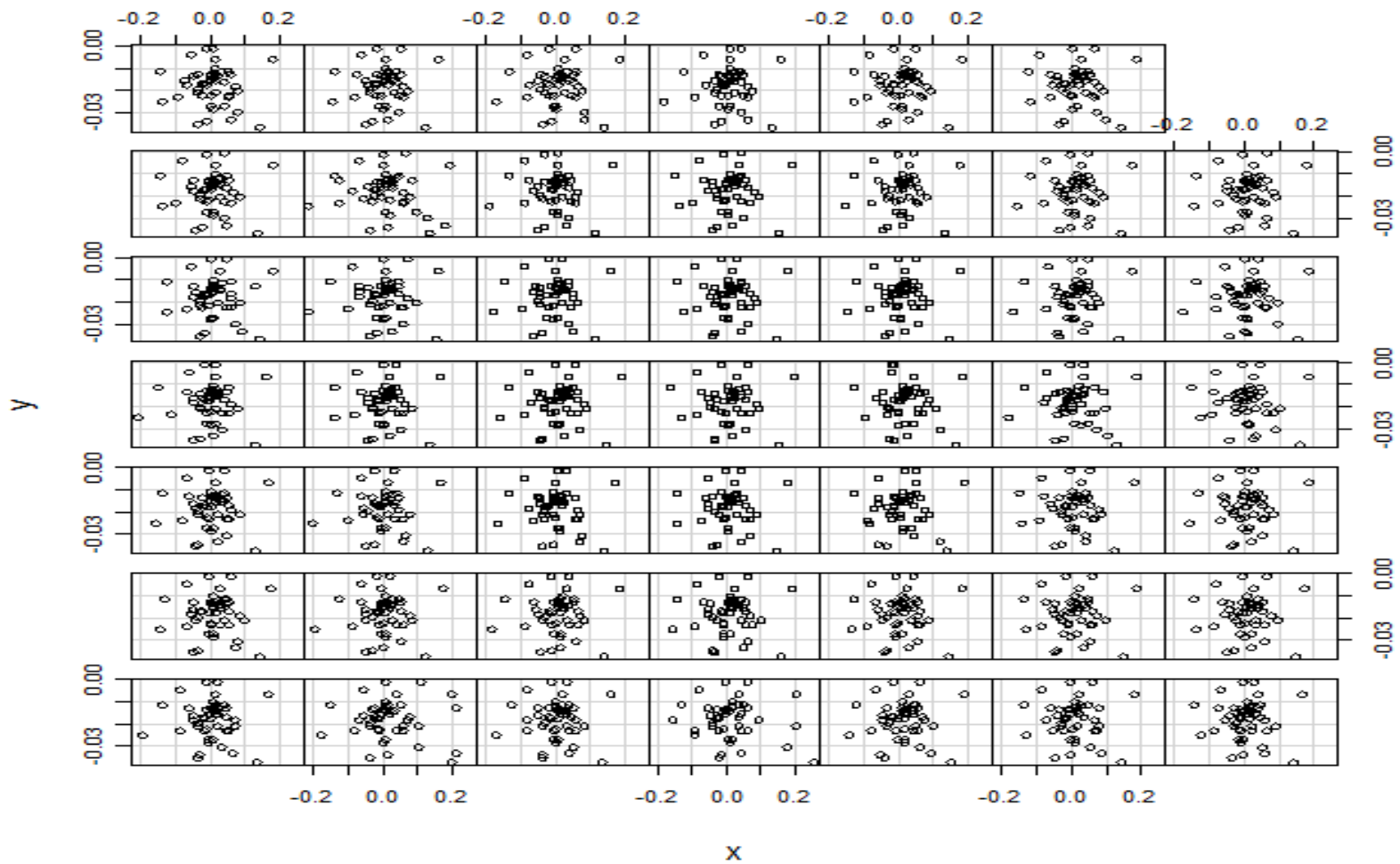


Figure 4.8. Panel Data for Equation (4.4b) at US States Level (except for Hawaii and Alaska), 1960-2007

Note: Y_{it} = the inflation adjusted interest rate, X_{it} = the real growth of disposable income

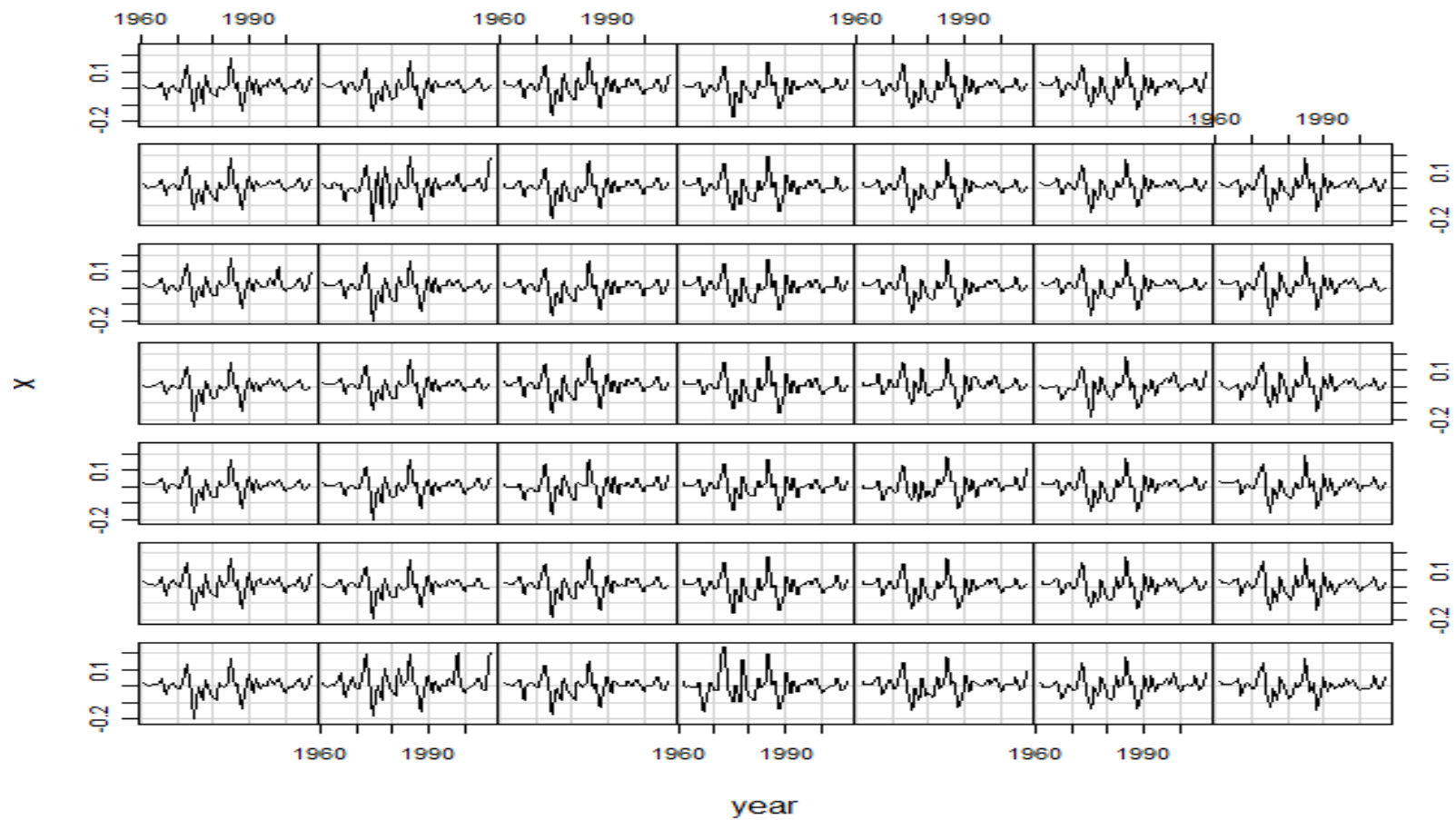


Figure 4.8. Continued

Note: X_{it} = the real growth of disposable income

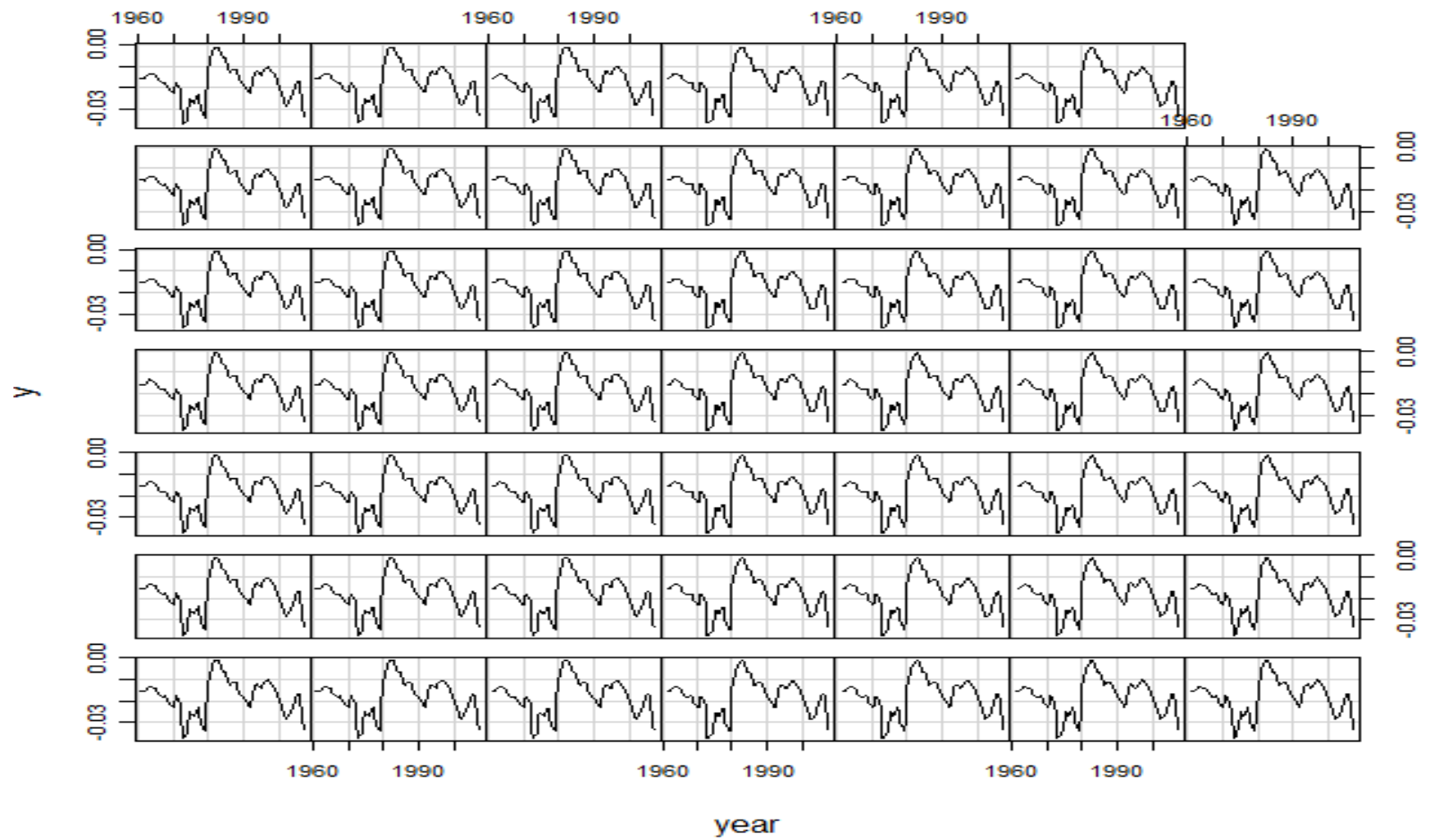


Figure 4.8. Continued

Note: Y_{it} = the inflation adjusted interest rate

4.3.2. Estimation Approach

In order to obtain an estimable form of the model developed in section II, we take the natural log on both sides of system (4.2):

$$V_{1it} = \ln(2 - \tilde{\alpha}_{IV} / \rho) + \ln[(q_{it} / q_{i,t+1})(\lambda R_{i,t+1}) / (\bar{r}_i + 1)] + (\rho - 1) \ln(y_{i,t+1} / y_{it}) \quad (4.3a)$$

$$V_{2it} = \ln(2 - \tilde{\alpha}_{IV} / \rho) + \ln[(q_{it} / q_{i,t+1})(1 + r_{i,t+1}) / (\bar{r}_i + 1)] + (\rho - 1) \ln(y_{i,t+1} / y_{it}) \quad (4.3b)$$

$$V_{3it} = \ln(2 - \tilde{\alpha}_{IV} / \rho) + \ln[(q_{it} / q_{i,t+1})(\partial \pi_{i,t+1} / \partial a_{it} + (p_{i,t+1} + v_{i,t+1})) / (\bar{r}_i + 1)] + (\rho - 1) \ln(y_{i,t+1} / y_{it}) - \ln((p_{i,t} + v_{i,t})) \quad (4.3c)$$

where $V_{1it} = \ln(1 - U_{1it})$, $V_{2it} = \ln(1 - U_{2it})$, and $V_{3it} = \ln(p_{i,t} + v_{i,t} - U_{3it}) - \ln(p_{i,t} + v_{i,t})$

Rearrange system (4.3), we have the following seemingly unrelated regression

$$\ln[(q_{it} / q_{i,t+1})(\lambda R_{i,t+1}) / (\bar{r}_i + 1)] = \dot{\alpha}(Z_{it}) + \dot{\rho} \ln(y_{i,t+1} / y_{it}) + V_{1it} \quad (4.4a)$$

$$\ln[(q_{it} / q_{i,t+1})(1 + r_{i,t+1}) / (\bar{r}_i + 1)] = \dot{\alpha}(Z_{it}) + \dot{\rho} \ln(y_{i,t+1} / y_{it}) + V_{2it} \quad (4.4b)$$

$$\ln[(q_{it} / q_{i,t+1})(\frac{\partial \pi_{i,t+1}}{\partial a_{it}} + (p_{i,t+1} + v_{i,t+1})) / ((\bar{r}_i + 1)(p_{i,t} + v_{i,t}))] = \dot{\alpha}(Z_{it}) + \dot{\rho} \ln(\frac{y_{i,t+1}}{y_{it}}) + V_{3it} \quad (4.4c)$$

where $\dot{\alpha} = -\ln(2 - \tilde{\alpha}_{IV} / \rho) = -\ln(2 - g(Z_{it}) / \rho) = \dot{\alpha}(Z_{it})$ and $\dot{\rho} = (1 - \rho)$

Equation (4.4b) is of the form of a popular semi-parametric specification of a partially linear model (Robinson 1988; Stock 1989):

$$Y_{it} = \dot{\alpha}(Z_{it}) + \dot{\rho} X_{it} + V_{it}$$

As we can see in equation (4.4b), Y_{it} denotes the inflation adjusted interest rate, and X_{it} denotes the real growth in disposable income. Figure 4.8 shows the interest rate and real growth panel data used in equation (4.4b) at US States level during 1960-2007. They are Y_{it} versus X_{it} , X_{it} versus year, and Y_{it} versus year. It is obvious that the

relationship between Y_{it} and X_{it} may not be best estimated as a linear one, and the non-parametric form provides flexibility to capture this nonlinearity in data.

We first obtain a consistent estimate of the smooth coefficient $\dot{\alpha}(Z_{it})$ from the following form of equation (4.4b) (Li et al 2002). Then, we substitute the estimated smooth coefficient $\hat{\alpha}(Z_{it})$ into the above system and estimate the rest of the coefficients as parameters in a seemingly unrelated regression (Henderson et al 2010). GMM will provide a consistent and efficient estimate for the system with covariance matrix information (Hansen 1982).

4.4. Estimation Results

The smooth coefficient model is estimated with R General user interface (RGui) 2.13.1 and our script is listed in Appendix G. The estimation results with the variables of temperature, precipitation and government payments respectively are summarized in table 4.1. For those 3 models, the estimation uses 2256 training points of 1 explaining variable in the smooth coefficient, with fixed bandwidth, and second-order Gaussian kernel.

Table 4.1. Summary of Smooth Coefficient Model Estimations

	Explanatory Variable Used in the Nonparametric Form		
	GP	Temp	Rain
Bandwidth	58125.0500	5648.5890	4.1212
Residual standard error	6.7509e-05	6.8715e-05	6.7242e-05
R-squared	1.9833e-02	6.1531e-04	2.3673e-02
Intercept Mean	-1.7940e-02	-1.7913e-02	-1.7853e-02

Note: The above results are retrieved with R command
`model.scoef <- npscoef(y ~ x| Z, betas = TRUE, data = panel).`
y = the inflation adjusted interest rate,
x = the real growth of disposable income,
Z = the variable used in the nonparametric form

4.4.1. Bandwidth

First we review the bandwidth calculations with all 3 variables, and compare their plots to identify the best model among the 3. Second, we look at the bandwidth calculation of the best model, and discuss the results in that model.

The bandwidth is calculated using R command "npscoefbw", and the smooth coefficient is calculated using "npscoef". Both commands are referred to Li and Racine (2007b), who proposed a data-driven cross-validatory bandwidth selection method. This method can handle the presence of potentially irrelevant regressors, and increase efficiency in finite-sample estimation. Table 4.1 reports the bandwidth estimated for every variable used in the model. Figure 4.9, 4.10, and 4.11 show us the distribution of calculated data in every bandwidth estimated in those models.

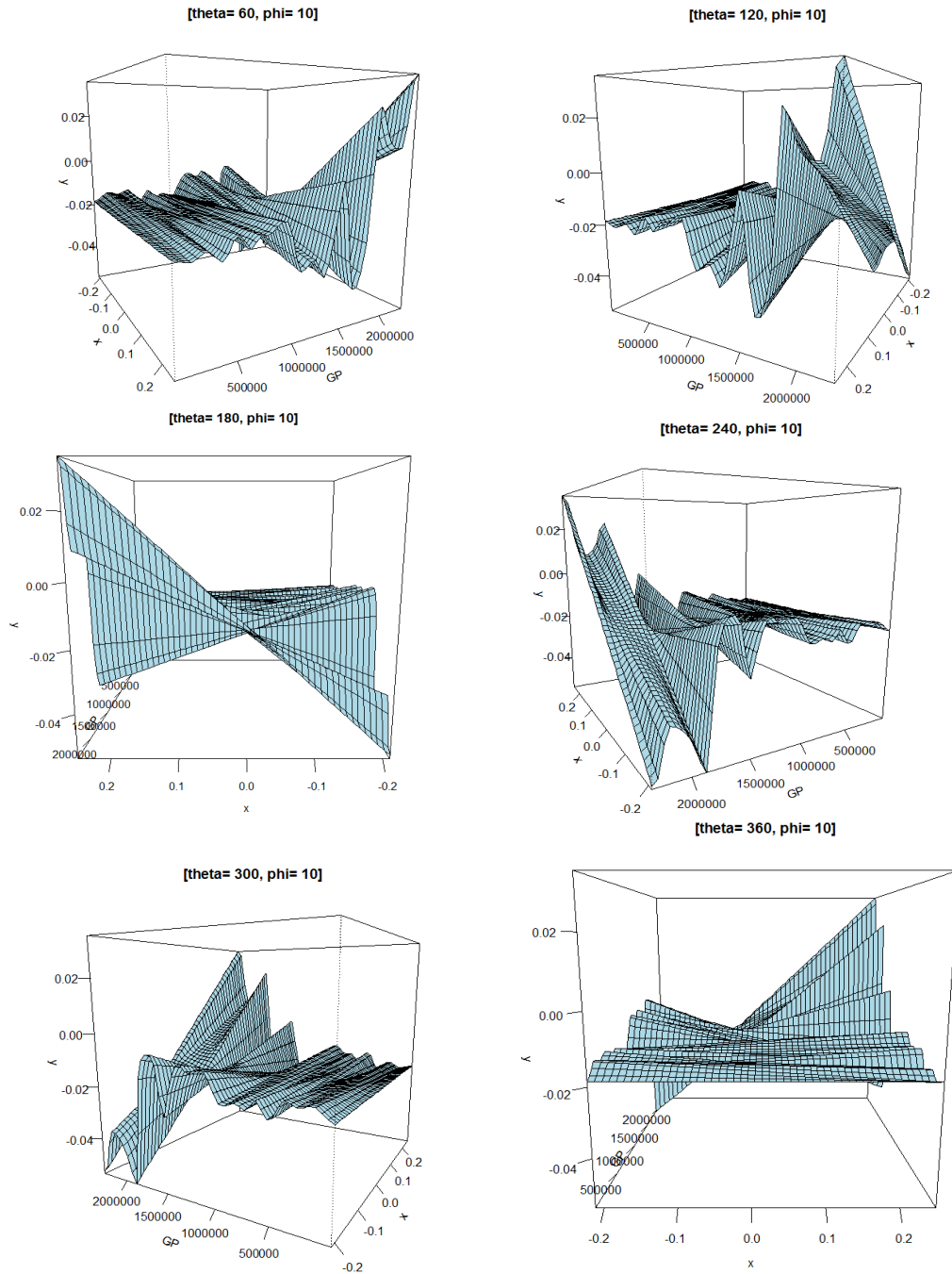


Figure 4.9. Computed Bandwidth for a Smooth Coefficient Kernel Regression Estimates with Government Payments as the Explanatory Variable in the Nonparametric Form

Note: The above results are retrieved with R command
`bw <- npscoefbw(formula=y~x|Z, data = panel).`
 y = the inflation adjusted interest rate,
 x = the real growth of disposable income,
 Z = direct government payments in thousands dollars

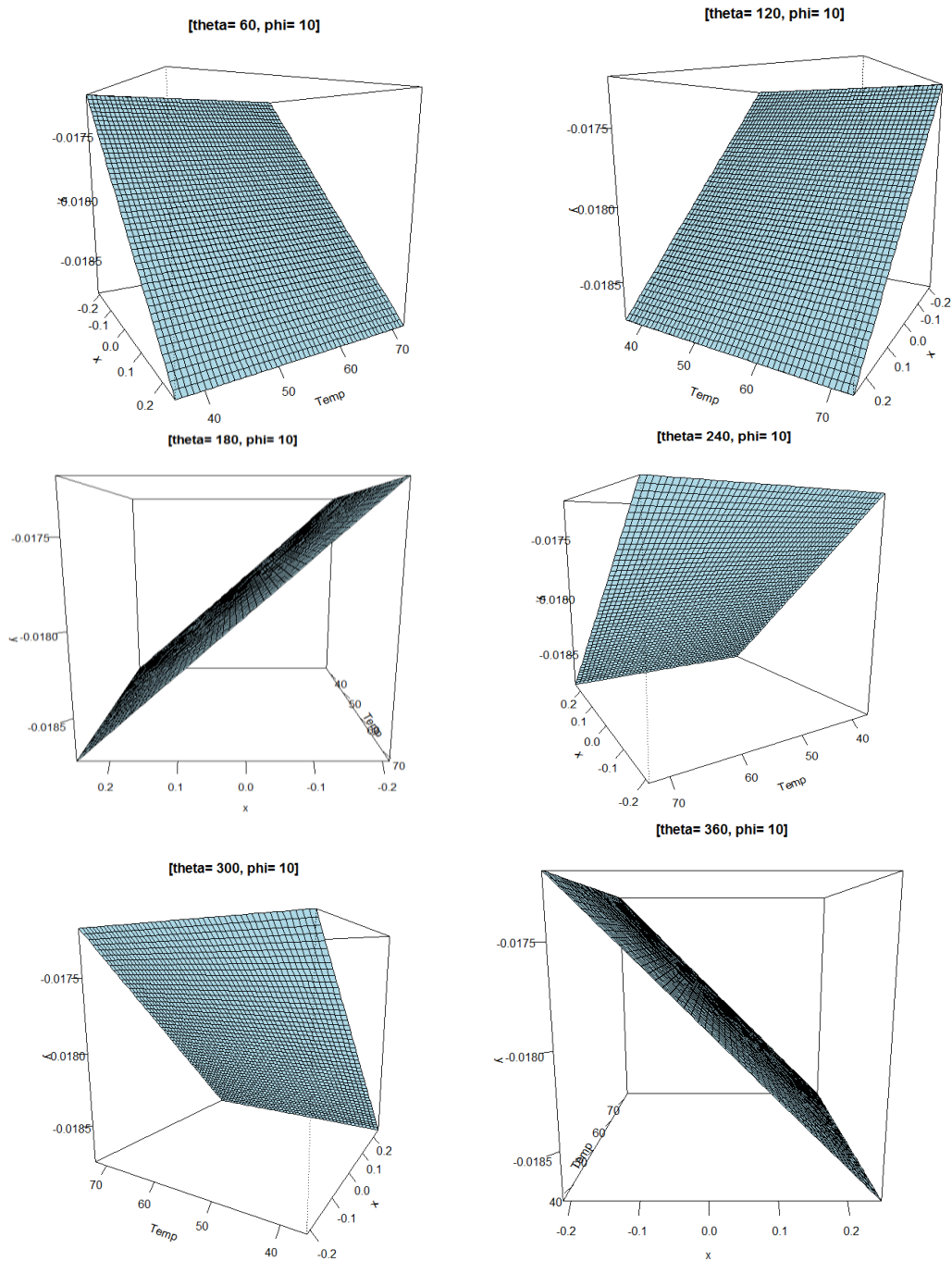


Figure 4.10. Computed Bandwidth for a Smooth Coefficient Kernel Regression Estimates with Temperatures as the Explanatory Variable in the Nonparametric Form

Note: The above results are retrieved with R command
`bw <- npscoefbw(formula=y~x|Z, data = panel).`
 y = the inflation adjusted interest rate,
 x = the real growth of disposable income,
 Z = average annual temperatures in degrees Fahrenheit

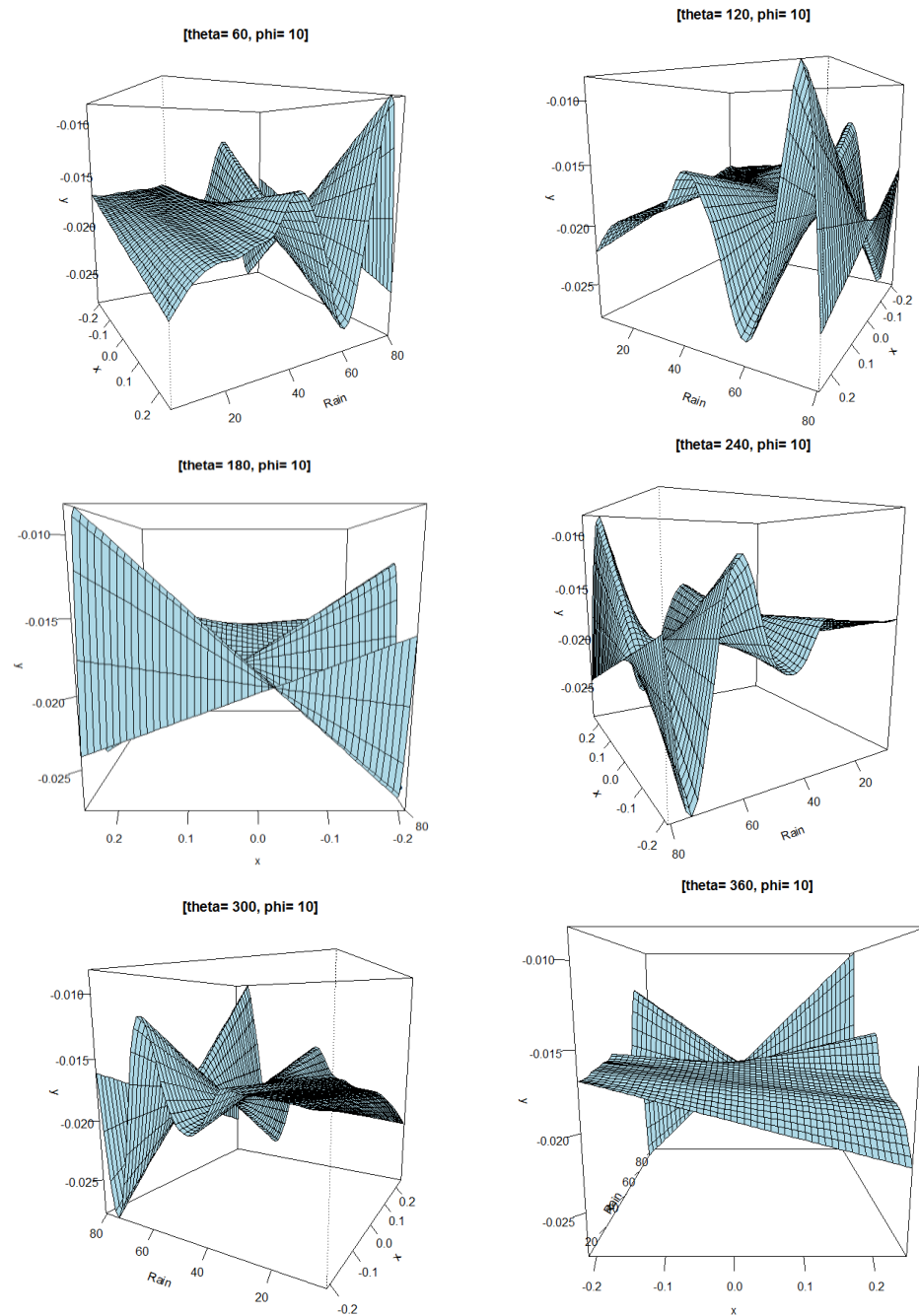


Figure 4.11. Computed Bandwidth for a Smooth Coefficient Kernel Regression Estimates with Precipitations as the Explanatory Variable in the Nonparametric Form

Note: The above results are retrieved with R command
`bw <- npscoefbw(formula=y~x|Z, data = panel).`
 y = the inflation adjusted interest rate,
 x = the real growth of disposable income,
 Z = annual precipitation in inches

Figure 4.9 shows the bandwidth for a smooth coefficient kernel regression estimate of equation (4.4b) with government payments (GP) as the explanatory variable. As we can see, Y_{it} changes significantly from bandwidth to bandwidth of GP over the range of X_{it} , which cannot be completely captured in a linear relationship. Figure 4.10 shows the bandwidth estimated with temperature as a variable. In contrast to figure 4.9, Y_{it} increases stably for every bandwidth of temperature over the range of X_{it} , which indicates a linear relationship between temperature and data. Figure 4.11 shows the bandwidth estimated with rain as a variable. Similar to figure 4.9, Y_{it} also changes significantly from bandwidth to bandwidth of rain over the range of X_{it} . However, the bandwidth plot of rain is much smoother than that of GP, which means that rain might be a better variable than GP in the model.

In short, figures 4.9, 4.10, and 4.11 reveal that Rain appears to yield a reasonable bandwidth selection with “npscoefbw” among the 3 variables. In contrast, the bandwidth selection with GP appears to be undersmoothing, leading to too many false modes, while the bandwidth selection with Temperature appears to be oversmoothing, leading to a linear estimate that obscures the possible nonlinear nature of the underlying distribution (Li and Racine 2007a, section 1.3.3). Here the mode of a continuous probability distribution is the value of a variable at which its probability density function has its maximum value, or, the mode is at the peak (Economic Statistics by Wikimedia Foundation).

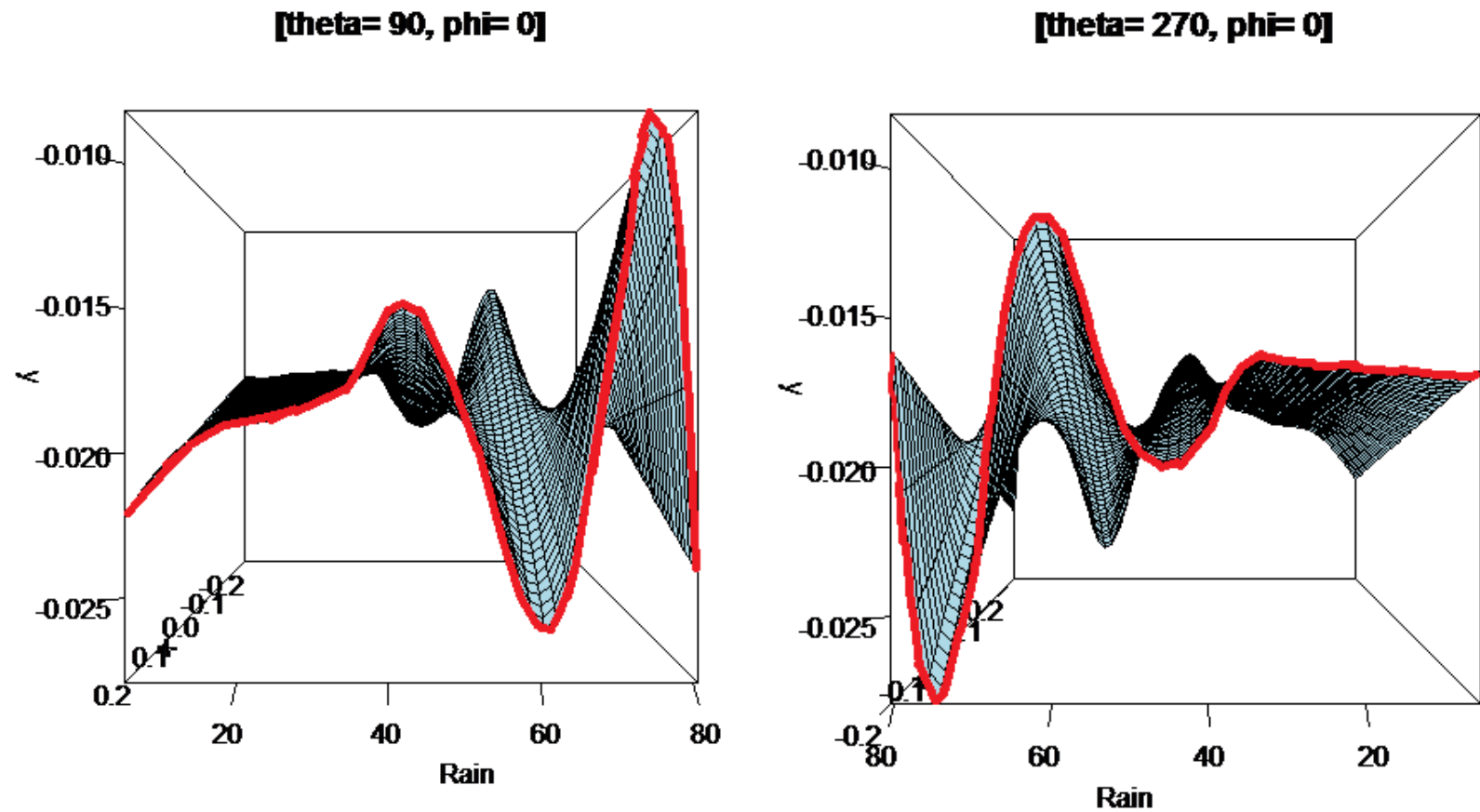


Figure 4.12. Estimates of the Impacts of Annual Precipitations on U.S. Farmland Valuations in a Smooth Coefficient Model

Note: The above results are retrieved with R commands:

```
model.scoef <- npscoef(y ~ x | Z)
plot(model.scoef)
```

y = the inflation adjusted interest rate,
x = the real growth of disposable income,
Z = annual percipiation in inches

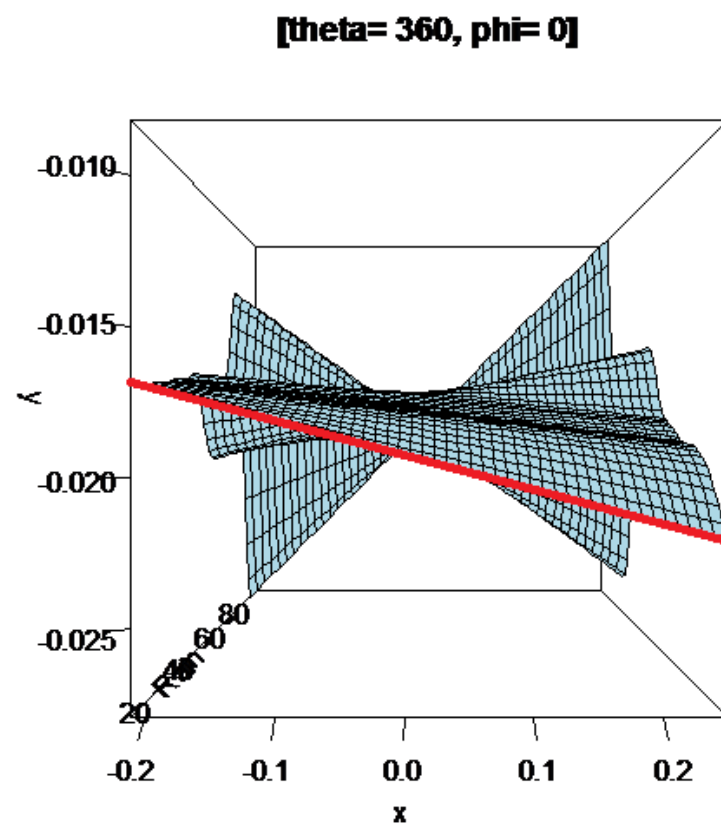
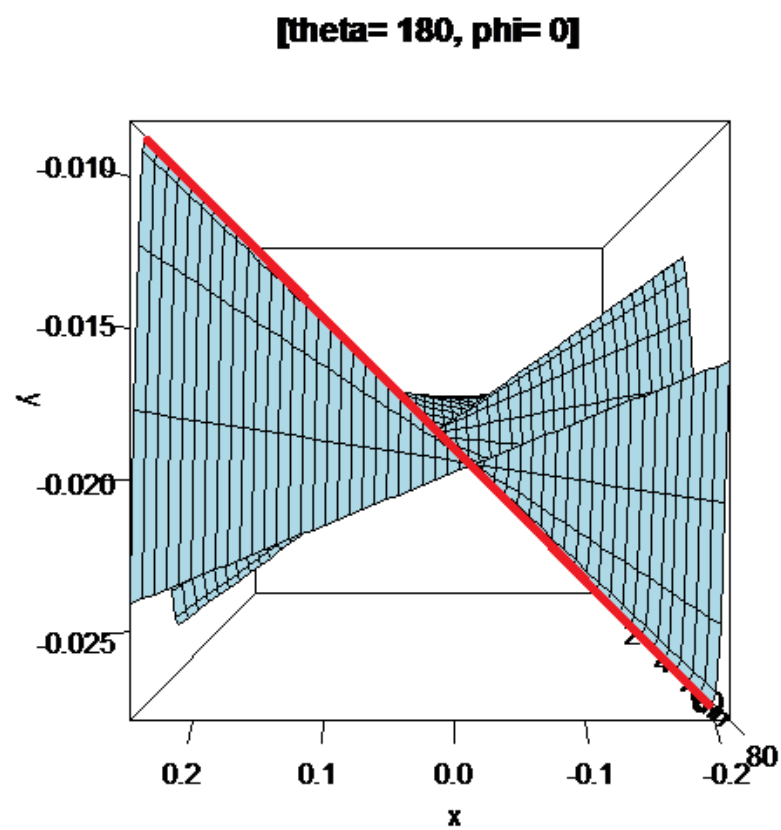


Figure 4.12. Continued

To further explain why temperature does not perform well as an independent variable in the non-parametric form, we would recall that figure 4.6 shows that the current measurement of temperature, annual average of the state in Fahrenheit degree, does not have enough variation in the model to justifiably represent the variable of temperature. Or, "annual average of the state in Fahrenheit degree" has lost most of the essential information in the variable of temperature in this case. Pertinent literature uses “degree days” (Mendelsohn, Nordhaus, and Shaw 1994) to measure temperature, and “degree days” could be a reasonable alternative measurement of temperature for the semi-parametric smooth coefficient model.

4.4.2. Economic Implications

Now we look at figure 4.12 to study the economic implications of the estimates of the smooth coefficient model using precipitations as an explanatory variable in the nonparametric form. R command “`model.scoef <- npscoef(y ~ x| Z)`” estimates a smooth coefficient kernel regression:

$$Y_{it} = \dot{\alpha}(Z_{it}) + \dot{\rho}(Z_{it})X_{it} + V_{it}$$

and returns the predicted value of the dependent variable, \hat{Y}_{it}

where

Y_{it} = the inflation adjusted interest rate,

X_{it} = the real growth of disposable income,

Z_{it} = Rain_{it} = Annual Precipitation in inches.

We rewrite the estimation formula used in figure 4.12 into the plot equation:

$$\hat{Y}_{it} = \dot{\alpha}(Z_{it}) + \dot{\rho}(Z_{it})X_{it}$$

In other words, \hat{Y}_{it} is plotted as a function of X_{it} and Z_{it} , or Rain_{it} in figure 4.12. Therefore, the three dimensions in figure 4.12 are Y for \hat{Y}_{it} , X for X_{it} , and Rain for Rain_{it} .

When we omit the correlation restrictions between equations in system (4.4) in our semi-parametric approach, the seemingly unrelated regression (SUR) estimation is the same as that from equation (4.4b) (Henderson et al 2010). In the SUR we derived in Section III, equation (4.4b) and (4.4c) shares the same terms on the right hand side, except for the error terms. In other words, we could also use the plots of figure 4.12 to explain the left hand side of equation (4.4c) instead of equation (4.4b), since error terms are omitted in those plots. The left hand side of equation (4.4c) is the inflation adjusted farmland valuation growth. Figure 4.12 tells us the impact of rain on inflation adjusted farmland valuation growth over the range of growth of disposable income for a representative agent in farm sector.

To simplify our analysis, we could hold all other variables constant, and allow only the future farmland prices (\hat{Y}_{it}), disposable income growth (X_{it}), and rain (Rain_{it}) to vary, since the change of future farmland prices is a reasonable approximation of the change of \hat{Y}_{it} when all the other variables are fixed in the inflation adjusted farmland valuation growth. A plane of Y-Rain crossing axis X at a certain point shows the impacts of rain on future farmland prices at a certain disposable income growth rate, and it should be a smooth curve as indicated in the plot equation:

$$\hat{Y}_{it} = \dot{\alpha}(Z_{it}) + \dot{\rho}(Z_{it})X_{it}$$

A plane of Y-X crossing axis Rain at a certain point shows the relationship between future farmland prices and disposable income growth rate at a certain rain level, and it should be a straight line as indicated in the plot equation.

4.4.1.1. Booming Stage

We first look at plots [$\theta=90$, $\phi=0$]. The edge of the bandwidth plot toward us (highlighted in red) shows the impacts of rain on future farmland prices when disposable income growth rate is high as 0.3. In equilibrium, high growth rate in disposable incomes means high consumption growth, high investment growth, and a highly growing economy in the whole, so this scenario is the booming stage of the economy.

As we can see in this plot, the farmland prices increase as rain amounts increase from 0 to 50 inches, decrease as rain amounts increase from 50 to 60 inches, then increase again when rain amounts increase from 60 to 72 inches, and decrease again when rain amounts increase from 72 to 80 inches. The first increase in farmland prices corresponding to increase of rain (0-50) is straightforward. It is probably related to cost savings from irrigation and revenue increases from higher crop yields. The second increase in farmland prices corresponding to increase of rain (60-72) is probably the results of adaptation. When the amount of rain exceeds a certain threshold, say 60 inches, the land is too wet and is not suitable for certain kinds of production. Therefore, when the crop land receives rain more than 60 inches, the farmers may switch to different crops to adapt to this climate change. This adaptation in turn increases revenue

due to higher crop yields and or values, and corresponds to a new mode in farmland valuation.

Schlenker, Hanemann, and Fisher 2006 found a “valley” shaped effect of degree days ($8-32^{\circ}\text{C}$) on farmland values by the combination of degree days and its square terms. Schlenker and Roberts 2009 demonstrated a nonlinear effect of temperature on yields as an eighth-order polynomial. Although researchers have long realized the nonlinear nature of the effects of climate change, no direct nonlinear relationships have been found between rain and farmland prices. The bimodal effect of rain on farmland prices from our semi-parametric model is an interesting finding. First, the direct revenue effect of rain is already captured in the DLPM through the farmland income discounted, and the bimodal effect plotted here in $[\theta=90, \phi=0]$ shows the risk aversion effect of climate change on farmland prices. This finding detangles the revenue effect from the risk aversion effect of climate change. Second, the nonparametric form gives us more flexibility in estimation and allows us to explore the true structure of data that might be otherwise omitted in a parametric approach. Third, we use dollar amount in our variable measurements, which prevents omitting important crops and their yields’ effect on farmland values.

4.4.1.2. Recession Stage

Next, we look at plot $[\theta=270, \phi=0]$. The edge of the bandwidth plot toward us (highlighted in red) shows the impacts of rain on future farmland prices when disposable income growth rate is low as -0.2 . In equilibrium, low growth rates in

disposable incomes, means low consumption growth, low investment growth, and a shrinking economy in the whole, so this scenario represents the recession stage of the economy.

As we can see in this plot, the impacts of rain on farmland prices almost reverse from those in the booming economy. The future farmland prices remain constant as rain amounts increase from 0 to 30 inches, decrease as rain amounts increase from 30 to 40 inches, increase as rain amounts increase from 40 to 60 inches, then decrease again when rain amounts increase from 60 to 72 inches, and increase again when rain amounts increase from 72 to 80 inches .

The differences between the rain's effects on farmland prices in the booming stage and the recession stage could be explained by the differences of crops planted by farmers in the two different stages. First, in the recession stage, the farmers will choose more economical crops in production. Not only the crops are cheaper to sell to consumers in a market, they are also more cost efficient in production. That is probably why we do not observe an increase in farmland prices when the rain amounts increase from 0-30 inches. And when rain amounts exceed 30 inches, those crops become less cost efficient, till first adaptation occurs at 40 inches, and second adaptation at 72 inches. Second, in the recession stage, the farmers will adopt less varieties and scales of crops in production. This explains the less stable or shorter trend of rain's effects on farmland prices. In the booming stage, farmland prices go through 4 trends as rain amounts range from 0-80 inches, while in the recession stage, farmland prices go through 5 trends in the same range of rain amounts.

4.4.1.3. Rain Abundant Region

Next, we look at plot [$\theta=180$, $\phi=0$], and the edge of the bandwidth plot (highlighted in red) shows the impacts of disposable income growth rate on future farmland prices when the rain amount is high as 75 inches. This plot shows that the future farmland prices increase significantly as disposable income growth rate increases. It is intuitive that the farmland prices in a productive region are highly sensitive to the economy cycle. When the economy is booming, the future farmland prices will increase a lot, and when the economy is in recession, the future farmland prices will decrease a lot.

4.4.1.4. Rain Scarce Region

Last, we look at plot [$\theta=360$, $\phi=0$], and the edge of the bandwidth plot toward us (highlighted in red) shows the impacts of disposable income growth rate on future farmland prices when the rain amount is low as 0 inches. This plot shows that the future farmland prices decrease slightly as disposable income growth rate increases. It is apparent that crops could not grow on farmland without irrigations in a region of 0 inch rain. When the economy is booming, more farmland will be used in the production. The increased cost of recourses, such as irrigation, and decreased prices of crops, due to higher yields, could all contribute to a low farmland price for those regions in a booming stage.

The angle system used in figures 4.9-4.12 are the so-called "x-convention," the most common definition of the rotation given by Euler angles (ϕ , θ , ψ),

where

- the first rotation is by an angle ϕ about the z-axis (here Y) using D,
- the second rotation is by an angle θ in $[0, \pi]$ about the former x-axis (here X) using C, and
- the third rotation is by an angle ψ about the former z-axis (here Y') using B.

(Not applied in figure 4.9, 4.10, or 4.11)

$$\mathbf{D} \equiv \begin{bmatrix} \cos \phi & \sin \phi & 0 \\ -\sin \phi & \cos \phi & 0 \\ 0 & 0 & 1 \end{bmatrix},$$

$$\mathbf{C} \equiv \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \theta & \sin \theta \\ 0 & -\sin \theta & \cos \theta \end{bmatrix},$$

$$\mathbf{B} \equiv \begin{bmatrix} \cos \psi & \sin \psi & 0 \\ -\sin \psi & \cos \psi & 0 \\ 0 & 0 & 1 \end{bmatrix}.$$

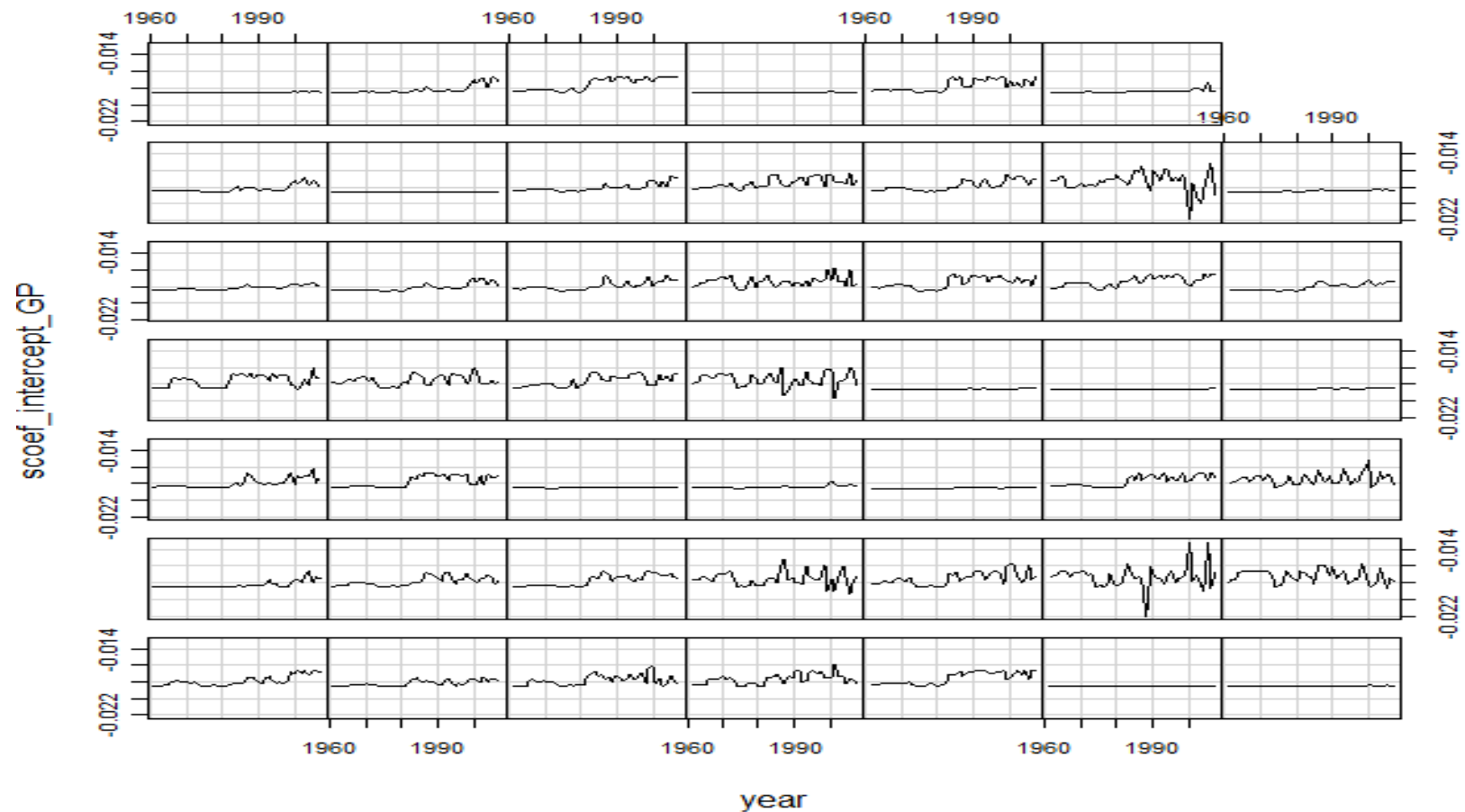


Figure 4.13. Estimates of the Smooth Coefficient $\hat{\alpha}(Z_{it})$ with Government Payments as the Explanatory Variable in the Nonparametric Form

Note: The above results are retrieved with R commands: `model.scoef <- npscoef(y ~ x | Z)`
`scoef_intercept <- coef(model.scoef)[,1]`
 y = the inflation adjusted interest rate, x = the real growth of disposable income, and Z = direct government payments in thousands dollars

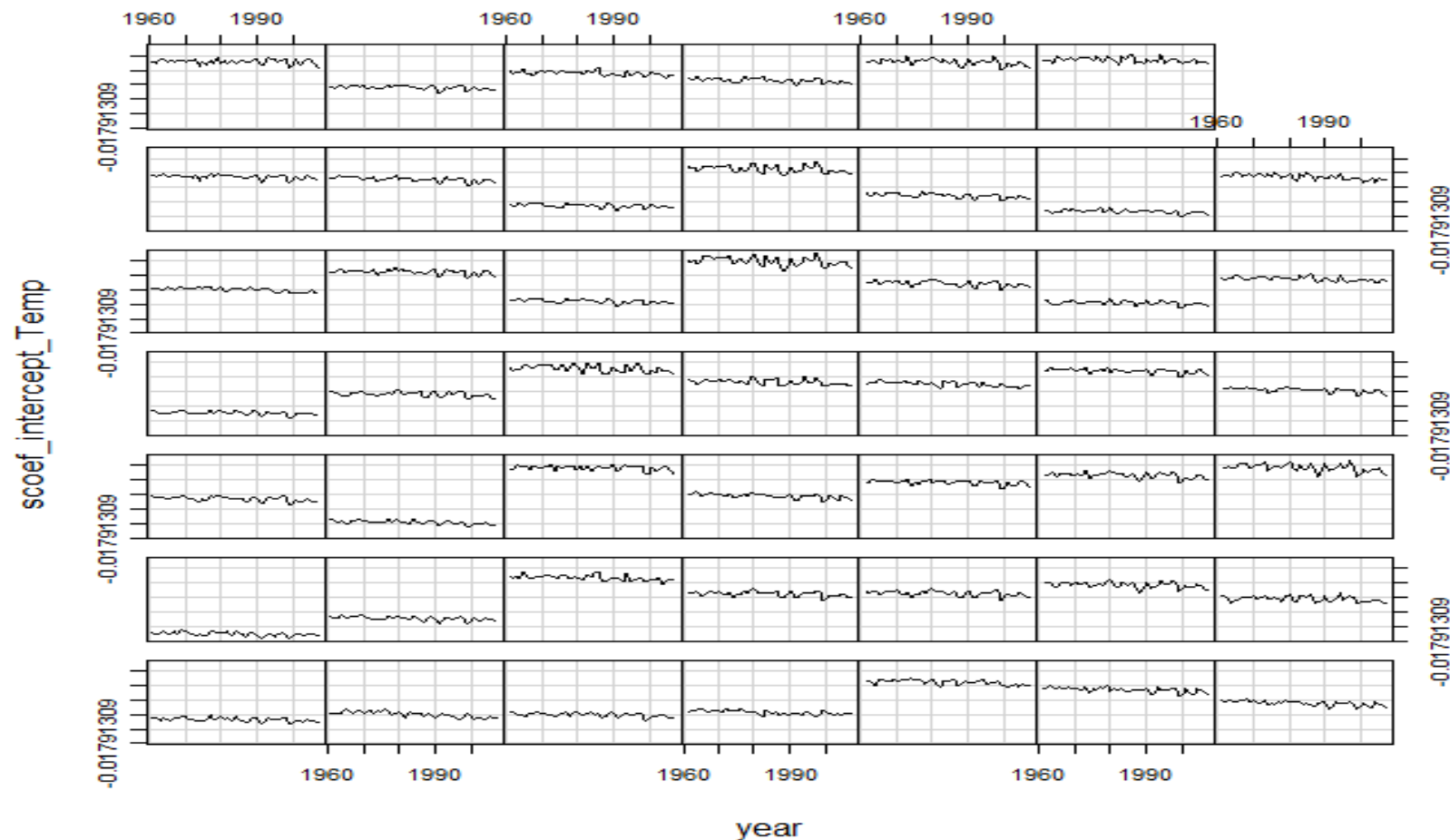


Figure 4.14. Estimates of the Smooth Coefficient $\hat{\alpha}(Z_{it})$ with Temperatures as the Explanatory Variable in the Nonparametric Form

Note: The above results are retrieved with R commands: `model.scoef <- npscoef(y ~ x | Z)`
`scoef_intercept <- coef(model.scoef)[,1]`
 y = the inflation adjusted interest rate, x = the real growth of disposable income, and Z = average annual temperatures in degrees Fahrenheit

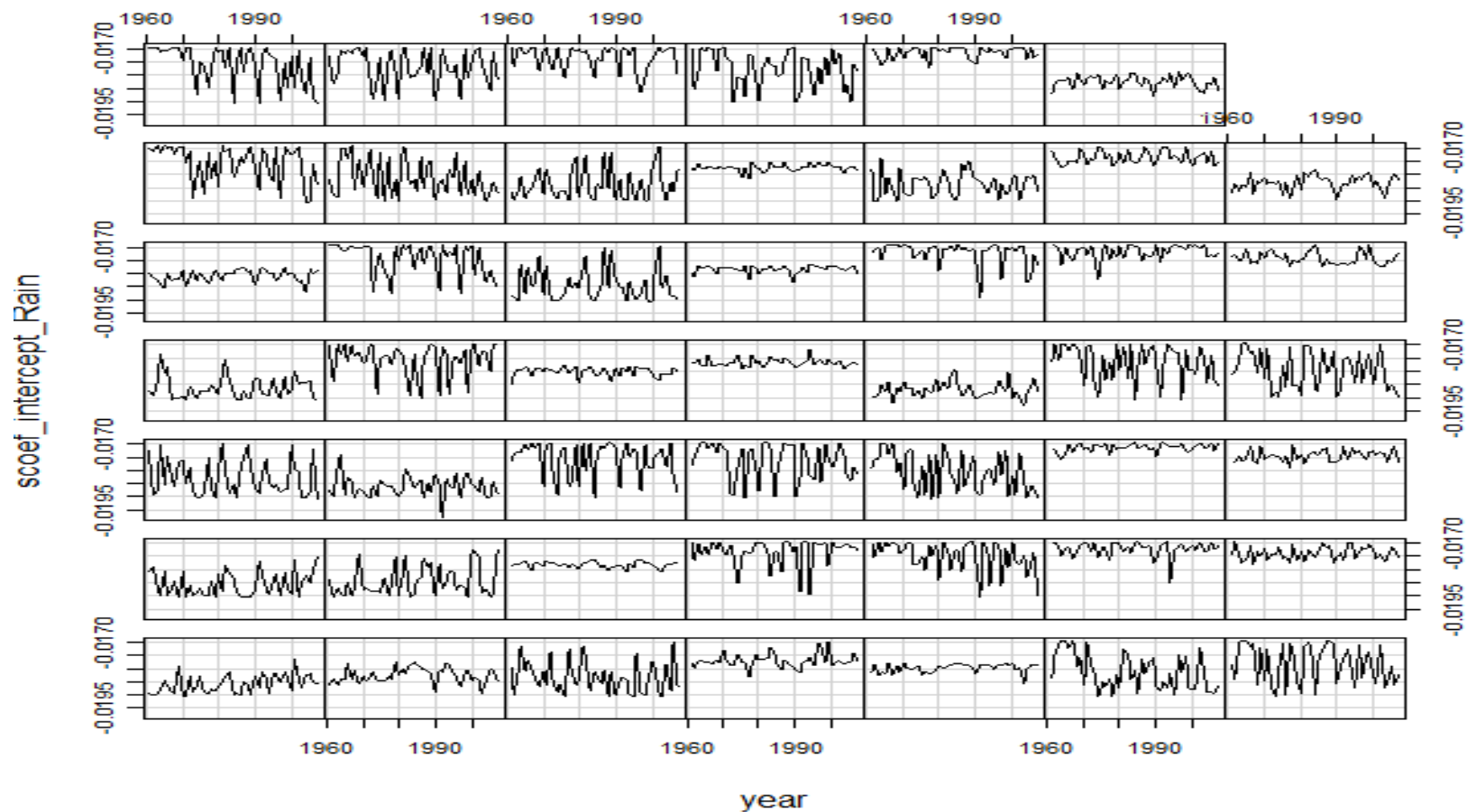


Figure 4.15. Estimates of the Smooth Coefficient $\hat{\alpha}(Z_{it})$ with Precipitations as the Explanatory Variable in the Nonparametric Form

Note: The above results are retrieved with R commands: `model.scoef <- npscoef(y ~ x | Z)`
`scoef_intercept <- coef(model.scoef)[,1]`
 y = the inflation adjusted interest rate, x = the real growth of disposable income, and Z = annual precipitations in inches

4.4.2. Estimation

Although table 4.1 shows that the mean of the estimated intercept $\hat{\alpha}(Z_{it})$ is not sensitive to the variable used in the model, figure 4.13, 4.14, and 4.15 tell us that both the range and the shape of the estimated intercept are significantly different in those models. As figure 4.13 shows, the estimated intercept $\hat{\alpha}(Z_{it})$ with GP as IV ranges from -0.022 to -0.014, and it has significantly more variations in the later years than the early years. As figure 4.14 shows, the estimated intercept $\hat{\alpha}(Z_{it})$ with temperature as IV stays closely to its mean, and it demonstrates a linear random effect estimation of the panel model. Figure 4.15 shows the estimated intercept $\hat{\alpha}(Z_{it})$ with rain as IV. The intercept varies a lot in some states, ranging from -0.0195 to -0.0170, but stays closely to its mean in others.

Corresponding to our analysis of bandwidth, we look at figure 4.15 to study the Chapter 4 section III, $\hat{\alpha} = -\ln(2 - \tilde{\alpha}_{IV} / \rho) = -\ln(2 - g(Z_{it}) / \rho) = \hat{\alpha}(Z_{it})$, and in Chapter 2 section II, α reflects the risk aversion of a representative agent. Therefore, in our semi-parametric model, the intercept captures risk aversion of the farmers, and it is denoted as a nonparametric form of Z_{it} , or Rain_{it} in figure 4.15. Figure 4.15 presents the estimated intercept over years 1960-2007 across states. As we can see, in most states, the estimated intercept changes significantly over the years, meaning that the risk aversion is time variant in those states. Further, the shape of the intercept differs significantly from state to state, which means that the risk aversion is heterogeneous among the states in US. This finding on time and space heterogeneity of risk aversion is consistent with

existing researches (Mendelsohn, Nordhaus, and Shaw 1994, Schlenker, Hanemann, and Fisher 2006), since Mendelsohn, Nordhaus, and Shaw 1994 have documented the heterogeneous impacts of climate change in time, and Schlenker, Hanemann, and Fisher 2006 in space.

The estimated intercept in figure 4.15 is denoted as a nonparametric form of Rain_{it} . This figure tells us that rain has a heterogeneous effect on future farmland prices (Y_{it}) through the intercept, or risk aversion of the farmers. Recall that figure 4.11 shows the correlation between farmland prices and rain amounts through bandwidth distribution; figure 4.15 organizes the estimated intercepts as a function of rain amounts in a year-state panel, to illustrate the mechanism of this correlation. Figure 4.15 specifically demonstrates the risk aversion effect of rain on farmland prices.

In short, these results confirm our hypothesis that risk aversion (captured in the intercept) changes across states and time periods. In other words, the semi-parametric approach allows risk aversion to vary and it does vary in reality. Our model effectively captures this variation in the risk aversion coefficient in its estimation, and makes our model robust against risk aversion misspecifications in panel data.

After estimating the smooth coefficient of intercept in the semi-parametric model, we substitute the estimated intercept $\hat{\alpha}(Z_{it})$ into the panel data, and estimate the parametric coefficients in a SUR panel model using EView 7. GMM estimator uses the long term covariance matrix as a weighting matrix in the regression, and generates an efficient estimate for the model. Since government payments and climate change are not used in

the parametric estimation, we do not report the GMM results in this chapter. But GMM panel results are consistent with those from the time series model.

4.5. Conclusion

Our results indicate that government payments and Climate change affect the change in farmland valuation through discounted revenues and the discounting factors, the latter which includes interest rate, inflation, time preference, and risk aversion. While interest rate, inflation, and time preference are well captured by the literature on farmland pricing, the heterogeneity of risk aversion among the agents on farmland markets is seldom considered. This essay shows that a non-parametric form for RAC could be an effective instrument against risk aversion misspecifications in dynamic farmland pricing models.

We find that precipitation is a good explanatory variable for the smooth coefficient semi-parametric model to study the risk aversion effect of climate change. In particular, rainfall affects land values in a bimodal nature in a boom economy, with the first mode at 40 inches per year and second at 70. The bimodal nature indicates that farmland prices could have multiple peaks in precipitation due to farmers' adaption to the amount of precipitation through crop selection and technology alternation. As a cautionary note, we have few observations on rainfall exceeding 70 inches per year, where the second mode of farmland valuation is at. Our estimation may be less confident in this portion of the data. Additional issues related to aggregation within each state have

not been addressed here and may also account for the bimodal relation between farmland valuation and rainfall.

Our estimation shows that annual precipitation in inches affect the inflation adjusted farmland valuation growth rate in US states through a time and space variant intercept of -0.0195 to -0.0170. This modest variation of the intercept in farmland valuation growth rate is generally not captured by previous works in the area (Mendelsohn, Nordhaus, and Shaw 1994; Schlenker, Hanemann, and Fisher 2006). Failure to recognize this variation might cause distortion in our understanding in farmland valuation, potentially leading to inaccurate assessments of consequences in areas of crop insurance and other general government policies.

In short, we demonstrate that land valuation has two paths of causal influence: first, climate change and government payments influence land valuation through discounted revenues, and second, land values are influenced by way of risk aversion of heterogeneous agents which in turn are influenced by climate factors. It is this second path of influence by climate factors that is our primary contribution of this chapter, as others have identified the first path in previous works.

Additional work could be done by including climatic extremes data, such as Palmer Drought Severity Index and extreme high low temperature days, in the nonparametric form as done in section III. Another limitation is that we omit soil types in our model. All explanatory variables are measured in monetary units and not crop yields. Further research could investigate the effects of varying soil types, which could further illustrate the effects of climate change on farmland valuations. Moreover, the

Euler equation model used in this chapter hardly captures the effects of temperature through RAC. This failure is mainly related to the fact that temperature does not vary much over the time period while farmland revenue does. Use of the nonparametric form in a longer-run panel setting to consider broader effects of climate change as they act across the panel would be a useful extension. The issue to be investigated in future research is that climate is a long-run phenomenon (Granger 1981), but it is used to account for changes in growth rate on a year to year basis as modeled here. Future research might profitably explore ways to model climate's effect on the long-run movement in growth rates.

CHAPTER V

CONCLUSION

The three essays of this dissertation use financial econometric models to study the three aspects of farmland valuation puzzle. Essay I addresses the short-term boom-bust cycles in farmland values, employing a general dynamic land pricing model under concave returns. Essay II examines overpricing of farmland utilizing a decomposition of the variances of the error terms from the essay I model, in the framework of quasi rational expectations. Essay III investigates the dual effects of direct government payments (DGP) and climate change on farmland values, in a semi-parametric coefficient model extended from essay I with panel data.

Essay I, “Asset Returns and Boom-Bust Cycles in Farmland Prices”, examines the causes of boom-bust cycles using a flexible DLPM using US farmland data. The model assumes general, instead of linear, homogeneity in budget constraint and profit function.

The estimated homogeneity degree of the profit function used in budget constraint demonstrates concavity, indicating diminishing reruns as land expands, and we mathematically prove that dynamic optimizations are likely to be unstable under concave returns. In other words, concavity of returns can result in embedded instability in farmland pricing. We also find that intertemporal elasticity of substitution, risk aversion, and transaction costs are important determinates for farmland value. Farmers’ willingness to delay consumption, as found through their high elasticity of substitution,

indicates they may be willing to hold on to land through bust cycles and thus raises the value of land and shortens the bust. High elasticity of substitution also means that farmers may be more willing to forgo consumption and acquire more land during a boom cycle prolonging the boom and inflating land values. Farmland price rigidity, related to low risk aversion in farmers, also helps to explain the prolonged boom stages and inevitability of bust stages in farmland valuation. While we find, as others have found (Chavas and Thomas 1999), that transaction costs vary across different stages of farmland valuation cycle, we argue these costs do not give rise to the cycle. That is to say, our explanation of the boom-bust cycle relates to diminishing returns, elasticity of substitution and risk aversion.

Our model generates better out-of-sample predictions than the linear homogeneity models, and provides empirical evidence of the connection between diminishing or concave returns with the boom-bust cycles in farmland prices. The DLPM framework under concave returns provides scholars a platform to calculate the stability range of the investment-consumption elasticity, and therefore better predict future boom-bust cycles in farmland prices.

Essay II, “The Value of Economic Information in Predictions of Farmland Prices”, is an analysis of the value of economic information. This analysis decomposes variance of farmland value predictions under quasi rational expectations with components from forward looking CAPM and back ward looking random walk.

This study first identifies structural changes in farmland prices over the period of 1970-2010, and then defines different stages according to those changing points. The

DLPM framework under concave returns (developed in Essay I) is adopted to generate predictions. The variance of the predictions is decomposed into the CAPM (forward) part and RW (backward) part. The moving average representation shows that in the short run, the CAPM portion of the variance of the forecast errors is significantly higher in a booming/busting stage than in a stable stage. This means that the market values the economic information more in an unstable stage than it does in a stable stage. However, the higher portion of the CAPM variance disappears quickly in the long run forecasts in a booming stage, which could be explained by the expected market adaptation. This finding is consistent with existing literature on the absorption behavior of economic information. The differential use of the information emanated from the CAPM model over the boom-bust farmland valuation cycle helps to explain the overpricing of farmland, but this explanation works primarily in the short run. Since CAPM explains different levels of uncertainty in the different stages of land valuation (i.e., boom, bust, and stable) the market is reacting differently to economic information through time. Thus time invariant representations of land valuation models do not capture the entire land valuation picture. We show that farmland values do respond to new information, but this response is not instantaneous.

Further research relating these notions to the mathematics of the characteristic equation (Box and Jenkins 1976) is certainly worthwhile. Also additional work contrasting FEVD from the nonlinear model with more structural linear model FEVD would be worth considering. Additional work could also be done with the orthogonalization of the error terms among different time series. The long run analysis

could be more meaningful with high frequency data, such as futures, stocks, and foreign exchanges.

Essay III, “The Dual Effects of Climate Change and Direct Government Payments on Farmland Valuation”, is a study on the dual effects of climate change and DGP on farmland prices. We extend the DLPM developed in Essay I to a panel data set of US states data in 1960-2007. This study allows heterogeneity of risk aversion across different places (US states) and time periods with a semi-parametric form. The parameter α , reflecting RAC, is defined as a smooth function of direct government payments and climate change, to make the panel model robust against risk aversion misspecifications.

We find that a non-parametric form of RAC could be an effective instrument against misspecifications of risk aversion in dynamic farmland pricing models. Precipitation is found to be a good candidate for the smooth coefficient semi parametric model to study the effects of climate change on farmland prices. In particular, rainfall is found to affect land values in a bimodal manner in a booming economy. Rainfall exhibits influences both through farmland prices and farmer risk aversion in rain abundant regions. Annual precipitations in inches affects the inflation adjusted farmland valuation growth in US states through a time and space variant intercept of $(-0.0195, -0.0170)$. This demonstrates that climate change and government payments influence land valuation through two paths: first, they influence land valuation through discounted revenues, and second, through the risk aversion of the farm sector.

Additional work could be done by including climatic extremes data, such as Palmer Drought Severity Index and extreme high low temperature days, in the nonparametric form as done in section III. Another limitation is that we omit soil types in our model. All explanatory variables are measured in dollar amounts. Further research could investigate the effects of varying soil types and crops plus use a longer run model, which could further illustrate the effects of climate change on farmland values.

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APPENDIX A

DEDUCTION OF FIRST ORDER CONDITIONS, EQUATION (15)

This appendix shows the deduction of equations (15a), (15b), and (15c) in Chapter II.

The deduction of (15a) is straight forward. All we need to do is to substitute (14a) and (14b) into the left hand side of (15a) as following

$$\begin{aligned}
 & \check{\beta} E_t[(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}] \\
 &= \beta g(\gamma) dE_t[(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}] \\
 &= \beta (E_t \dot{U}_{t+1}^\gamma)^{\frac{1}{\gamma}-1} E_t[\dot{U}_{t+1}^{\gamma-1}] \frac{E_t[\dot{U}_{t+1}^{\gamma-1}(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}]}{E_t[\dot{U}_{t+1}^{\gamma-1}] E_t[(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}]} E_t[(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}] \\
 &= \beta (E_t \dot{U}_{t+1}^\gamma)^{\frac{1}{\gamma}-1} E_t[\dot{U}_{t+1}^{\gamma-1}(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}]
 \end{aligned}$$

Then by equation (13a), we have the left hand side of equation (15a) equals to the right hand side of (15a), and deduction of equation (15a) is complete.

In order to deduct equation (15b) and (15c), we need to take the same approach as demonstrated above for equation (15a), except that we also need to prove two more conditions:

$$\frac{E_t[\dot{U}_{t+1}^{\gamma-1}(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}]}{E_t[\dot{U}_{t+1}^{\gamma-1}] E_t[(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}]} = \frac{E_t[\dot{U}_{t+1}^{\gamma-1}(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})(1+r_{t+1})]}{E_t[\dot{U}_{t+1}^{\gamma-1}] E_t[(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})(1+r_{t+1})]} \quad (A1)$$

$$\frac{E_t[\dot{U}_{t+1}^{\gamma-1}(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}]}{E_t[\dot{U}_{t+1}^{\gamma-1}] E_t[(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}]} = \frac{E_t[\dot{U}_{t+1}^{\gamma-1}(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})(\frac{\partial \pi_{t+1}}{\partial a_{j,t}} + (p_{j,t+1} + \nu_{j,t+1}))]}{E_t[\dot{U}_{t+1}^{\gamma-1}] E_t[(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})(\frac{\partial \pi_{t+1}}{\partial a_{j,t}} + (p_{j,t+1} + \nu_{j,t+1}))]} \quad (A2)$$

To prove (A1) and (A2), we construct a new function $f_t(a_{0,t}, a_{j,t})$, where

$$f_t(a_{0,t}, a_{j,t}) = G_{t+1} - R_{t+1} A_t \equiv 0$$

By the definition of G_t , A_t , and the homogeneity assumption expressed in equation (6), we write out $f_t(a_{0,t}, a_{j,t})$ as following:

$$\begin{aligned}
f_t(a_{0,t}, a_{j,t}) &= G_{t+1} - R_{t+1}A_t \\
&= (r_{t+1} + 1)a_{0,t} + \pi_{t+1}(a_{1,t}, \dots, a_{j,t}) + \sum_{j=1}^J [p_{j,t+1} + \nu_{j,t+1}]a_{j,t} \\
&\quad - K_{t+1} \left(a_{0,t} + \sum_{j=1}^J [p_{j,t} + \nu_{j,t}]a_{j,t} \right)^\lambda
\end{aligned}$$

Since $f_t(a_{0,t}, a_{j,t}) = 0$, $\forall (a_{0,t}, a_{j,t}) \in \{(a_{0,t}, a_{j,t}) | a_{0,t} \geq 0, a_{j,t} \geq 0\}$, we have the first order derivative

$$f'_t(a_{0,t}, a_{j,t}) = \begin{cases} \frac{\partial f_t(a_{0,t}, a_{j,t})}{\partial a_{0,t}} = r_{t+1} + 1 - \lambda R_{t+1} & = 0 \\ \frac{\partial f_t(a_{0,t}, a_{j,t})}{\partial a_{j,t}} = \frac{\partial \pi_{t+1}}{\partial a_{j,t}} + (p_{j,t+1} + \nu_{j,t+1}) - \lambda R_{t+1}(p_{j,t} + \nu_{j,t}) & = 0 \end{cases}$$

Rearrange the first order derivative, we have the following

$$\begin{aligned}
\lambda R_{t+1} &= r_{t+1} + 1 \\
\lambda R_{t+1} &= \frac{\frac{\partial \pi_{t+1}}{\partial a_{j,t}} + (p_{j,t+1} + \nu_{j,t+1})}{(p_{j,t} + \nu_{j,t})}
\end{aligned}$$

Substitute the above two equations into the definition of d , we can prove condition (A1) and (A2), and therefore deduct the equation (15b) and (15c).

APPENDIX B

DEDUCTION OF TIME-ADDITIVE PREFERENCES

This appendix shows the deduction of time-additive preferences in Chapter II.
By definition, we have

$$\begin{aligned}\beta' &= \beta d_1 d_2 d_3 \\ &= \beta (E_t \dot{U}_{t+1}^\gamma)^{\frac{1}{\gamma}-1} E_t[\dot{U}_{t+1}^{\gamma-1}] \frac{E_t[\dot{U}_{t+1}^{\gamma-1} (y_t/y_{t+1})^{1-\rho} (q_t/q_{t+1})^\lambda R_{t+1}]}{E_t[\dot{U}_{t+1}^{\gamma-1}] E_t[(y_t/y_{t+1})^{1-\rho} (q_t/q_{t+1})^\lambda R_{t+1}]}\end{aligned}$$

Now we discuss the values of β , d_1 , d_2 , and d_3 respectively.

First, according to neoclassical economics, we take the rate of time preference, $\delta = \frac{1}{\beta} - 1$ as a parameter in the utility function. The time discounting factor β captures the trade off between consumption today and consumption in the future, and is thus exogenous and subjective. In the long run steady state, the rate of interest equal the rate of time preference, with the marginal product of capital adjusting to ensure this equality holds. Arbitrage implies that $\delta = \frac{1}{\beta} - 1 = r$, where r is the long run return rate of riskless asset. Therefore, in the long run steady state we have:

$$\beta = \frac{1}{r+1} \tag{B1}$$

Second, when γ is close to 1, we could use the Taylor expansion to approximate the value of $g(\gamma) = d_1 d_2$.

$$\begin{aligned}g(\gamma) &= g(1) + (\gamma - 1)g'(1) + \text{other.small.term} \\ &\approx g(1) + (\gamma - 1)g'(1)\end{aligned} \tag{B2}$$

Since $g(\gamma) = (E_t \dot{U}_{t+1}^\gamma)^{\frac{1}{\gamma}-1} E_t[\dot{U}_{t+1}^{\gamma-1}]$, we take the first order derivative of $g(\gamma)$ respect to γ and get:

$$\begin{aligned} g'(\gamma) &= \frac{\partial((E_t \dot{U}_{t+1}^\gamma)^{\frac{1}{\gamma}-1} E_t[\dot{U}_{t+1}^{\gamma-1}])}{\partial \gamma} \\ &= \frac{\partial((E_t \dot{U}_{t+1}^\gamma)^{\frac{1}{\gamma}-1})}{\partial \gamma} E_t[\dot{U}_{t+1}^{\gamma-1}] + (E_t \dot{U}_{t+1}^\gamma)^{\frac{1}{\gamma}-1} \frac{\partial(E_t[\dot{U}_{t+1}^{\gamma-1}])}{\partial \gamma} \end{aligned} \quad (B3)$$

$$\begin{aligned} &\frac{\partial((E_t \dot{U}_{t+1}^\gamma)^{\frac{1}{\gamma}-1})}{\partial \gamma} \\ &= \ln(E_t \dot{U}_{t+1}^\gamma) (E_t \dot{U}_{t+1}^\gamma)^{\frac{1}{\gamma}-1} \left(-\frac{1}{\gamma^2}\right) + \left(\frac{1}{\gamma} - 1\right) (E_t \dot{U}_{t+1}^\gamma)^{\frac{1}{\gamma}-2} E_t[\ln(\dot{U}_{t+1}) \dot{U}_{t+1}^\gamma] \end{aligned} \quad (B4)$$

$$\begin{aligned} &\frac{\partial(E_t[\dot{U}_{t+1}^{\gamma-1}])}{\partial \gamma} \\ &= E_t[\ln(\dot{U}_{t+1}) \dot{U}_{t+1}^{\gamma-1}] \end{aligned} \quad (B5)$$

Substitute (B4) and (B5) into (B3), we have

$$\begin{aligned} g'(\gamma) &= (E_t \dot{U}_{t+1}^\gamma)^{\frac{1}{\gamma}-1} E_t[\dot{U}_{t+1}^{\gamma-1}] \left\{ \ln(E_t \dot{U}_{t+1}^\gamma) \left(-\frac{1}{\gamma^2}\right) + \left(\frac{1}{\gamma} - 1\right) \frac{E_t[\ln(\dot{U}_{t+1}) \dot{U}_{t+1}^\gamma]}{E_t[\dot{U}_{t+1}^\gamma]} + \frac{E_t[\ln(\dot{U}_{t+1}) \dot{U}_{t+1}^{\gamma-1}]}{E_t[\dot{U}_{t+1}^{\gamma-1}]} \right\} \\ &= g(\gamma) \left\{ \left(\frac{E_t[\ln(\dot{U}_{t+1}) \dot{U}_{t+1}^{\gamma-1}]}{E_t[\dot{U}_{t+1}^{\gamma-1}]} - \frac{E_t[\ln(\dot{U}_{t+1}) \dot{U}_{t+1}^\gamma]}{E_t[\dot{U}_{t+1}^\gamma]} \right) + \frac{1}{\gamma} \left(\frac{E_t[\ln(\dot{U}_{t+1}) \dot{U}_{t+1}^\gamma]}{E_t[\dot{U}_{t+1}^\gamma]} - \ln(E_t \dot{U}_{t+1}^\gamma)^{\frac{1}{\gamma}} \right) \right\} \end{aligned} \quad (B6)$$

Define $E_t[\ln(\dot{U}_{t+1})] - \ln(E_t \dot{U}_{t+1}) \equiv L$, where $L \leq 0$. Equation (B6) implies that

$$\begin{aligned} g'(1) &= g(1) \{E_t[\ln(\dot{U}_{t+1})] - \ln(E_t \dot{U}_{t+1})\} \\ &= L \end{aligned}$$

Substitute $g'(1)$ into equation (B2), we have

$$\begin{aligned} g(\gamma) &\approx g(1) + (\gamma - 1)g'(1) \\ &= 1 + (\gamma - 1)L \end{aligned} \quad (\text{B7})$$

Third, when γ is close to 1, $(\gamma - 1)$ is close to 0, $\dot{U}_{t+1}^{\gamma-1}$ is close to a constant, and $\text{cov}(\dot{U}_{t+1}^{\gamma-1}, (y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}) \approx 0$. Therefore,

$$\begin{aligned} d_3 &= \frac{E_t[\dot{U}_{t+1}^{\gamma-1}(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}]}{E_t[\dot{U}_{t+1}^{\gamma-1}]E_t[(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}]} \\ &= \frac{E_t[\dot{U}_{t+1}^{\gamma-1}]E_t[(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}] + \text{cov}(\dot{U}_{t+1}^{\gamma-1}, (y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1})}{E_t[\dot{U}_{t+1}^{\gamma-1}]E_t[(y_t/y_{t+1})^{1-\rho}(q_t/q_{t+1})\lambda R_{t+1}]} \\ &\approx 1 \end{aligned} \quad (\text{B8})$$

Finally, when we substitute (B1), (B7), and (B8) into the definition of β' , we have

$$\begin{aligned} \beta' &= \beta d_1 d_2 d_3 \\ &= \beta g(\gamma) d_3 \\ &\approx \frac{1}{r+1} (1 + (\gamma - 1)L) \times 1 \end{aligned} \quad (\text{B9})$$

Rearrange (B9) we have the following

$$(\gamma - 1)L = \beta'(r + 1) - 1 \quad (\text{B10})$$

Since $U_t = [(1 - \beta)y_t^\rho + \beta(E_t U_{t+1}^\alpha)^{\rho/\alpha}]^{1/\rho} = [(1 - \beta)y_t^\rho + \beta(E_t[(1 - \beta)y_{t+1}^\rho + \beta(E_{t+1} U_{t+2}^\alpha)^{\rho/\alpha}])^{\rho/\alpha}]^{1/\rho} = \dots$, U_t is linear homogeneous in $(y_t, y_{t+1}, y_{t+2}, \dots)$.

In other words, the optimization problem is not sensitive to the unit of consumptions and utility. Therefore, we could always find a utility unit, so that

$L = E_t[\ln(\dot{U}_{t+1})] - \ln(E_t \dot{U}_{t+1}) = E_t[\ln(\frac{U_{t+1}^\rho}{1-\beta})] - \ln(E_t[\frac{U_{t+1}^\rho}{1-\beta}]) = -1$. Then

equation (B10) could be rewritten as:

$$\gamma = 2 - \beta'(r + 1) \tag{B11}$$

APPENDIX C

SPECIAL CASES

This appendix discusses several special cases of the dynamic land pricing model in Chapter II.

As we have specified in Section 2 Chapter II, the traditional assumption of linear homogeneity of gross return function is unrestricted, and we assume general homogeneity in gross return function. Our general DLPM nests the linear homogeneity model as a special case of homogeneity. Further, our DLPM also nests several other models as special cases with specific values of parameters. Here we discuss four other special cases to illustrate the generality of our model.

In our model set up, we first define the utility framework as equation (2.3)

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

where $M_t = (E_t U_{t+1}^\alpha)^{1/\alpha}$

Then, in our specifications, we simplify the original utility framework into equation (2.8),

$$\dot{U}_t = y_t^\rho + \beta(E_t \dot{U}_{t+1}^\gamma)^{1/\gamma}$$

where $\dot{U}_t \equiv \frac{U_t^\rho}{1-\beta}$ and $\gamma \equiv \alpha/\rho$

In this section, we discuss several special cases nested in the general utility function form. When parameters α , ρ , and γ take some specific values such as 0 or 1, the general

utility function reduces to extreme risk aversion, risk neutrality, static CAPM, random walk, and expected time-additive utility forms respectively.

1. When $\alpha = 0$ or 1, and $1 > \rho > 0$

When $\alpha = 0$ and $1 > \rho > 0$, we have $\gamma = \frac{\alpha}{\rho} = 0$. Since

$$\lim_{\gamma \rightarrow 0} (E_t \dot{U}_{t+1}^\gamma)^{1/\gamma} = \exp(E_t[\ln \dot{U}_{t+1}])$$

Equation (8) reduces to the following special case for extreme risk aversion, $\alpha = 0$.

$$\begin{aligned} \dot{U}_t &= y_t^\rho + \beta (E_t \dot{U}_{t+1}^\gamma)^{1/\gamma} \\ &= y_t^\rho + \beta \exp(E_t[\ln \dot{U}_{t+1}]) \end{aligned} \quad (\text{S1})$$

When $\alpha = 1$ and $1 > \rho > 0$, we have $\gamma = \frac{\alpha}{\rho} = \frac{1}{\rho}$. Equation (8) reduces to the following special case for risk neutrality, $\alpha = 1$.

$$\begin{aligned} \dot{U}_t &= y_t^\rho + \beta (E_t \dot{U}_{t+1}^\gamma)^{1/\gamma} \\ &= y_t^\rho + \beta (E_t \dot{U}_{t+1}^{\frac{1}{\rho}})^\rho \end{aligned} \quad (\text{S2})$$

Equation (S1) and (S2) define two extremes of the risk aversion range for agents in the farmland market.

2. When $1 > \alpha > 0$, and $\gamma = 0$

To simplify notation, we define $\ddot{U}_t \equiv U_t^\alpha$, and $\ddot{y}_t \equiv y_t^\alpha$, then we have

$$\begin{aligned} M_t^\rho &= (E_t \ddot{U}_{t+1})^{1/\gamma} \\ \implies \ddot{U}_t &= [(1 - \beta) \ddot{y}_t^{1/\gamma} + \beta (E_t \ddot{U}_{t+1})^{1/\gamma}]^\gamma \end{aligned} \quad (\text{S3})$$

When $1 > \alpha > 0$ and $\gamma = 0$. Equation (S3) indicates the following:

$$\begin{aligned} \ln \ddot{U}_t &= \lim_{\gamma \rightarrow 0} \ln [(1 - \beta) \ddot{y}_t^{1/\gamma} + \beta (E_t \ddot{U}_{t+1})^{1/\gamma}]^\gamma \\ &= \lim_{\gamma \rightarrow 0} \frac{\ln [(1 - \beta) \ddot{y}_t^{1/\gamma} + \beta (E_t \ddot{U}_{t+1})^{1/\gamma}]}{1/\gamma} \\ &= \lim_{\gamma \rightarrow 0} \frac{(1 - \beta) \ddot{y}_t^{1/\gamma} \ln \ddot{y}_t + \beta (E_t \ddot{U}_{t+1})^{1/\gamma} \ln E_t \ddot{U}_{t+1}}{(1 - \beta) \ddot{y}_t^{1/\gamma} + \beta (E_t \ddot{U}_{t+1})^{1/\gamma}} \\ &= \lim_{\gamma \rightarrow 0} \frac{(1 - \beta) \ln \ddot{y}_t + \beta (E_t \ddot{U}_{t+1} / \ddot{y}_t)^{1/\gamma} \ln E_t \ddot{U}_{t+1}}{(1 - \beta) + \beta (E_t \ddot{U}_{t+1} / \ddot{y}_t)^{1/\gamma}} \end{aligned} \quad (\text{S4})$$

Assume $0 < \ddot{y}_t \leq E_t \ddot{U}_{t+1}$. When $\gamma \rightarrow 0^-$, equation (S4) reduces to the static CAPM case

$$\ddot{U}_t = \ddot{y}_t \quad (\text{S5})$$

When $\gamma \rightarrow 0^+$, equation (S4) reduces to the random walk case

$$\ddot{U}_t = E_t \ddot{U}_{t+1} \quad (\text{S6})$$

3. When $1 > \alpha = \rho > 0$

When $1 > \alpha = \rho > 0$, we have $\gamma = \frac{\alpha}{\rho} = 1$, and

$$\begin{aligned}\dot{U}_t &= y_t^\rho + \beta(E_t \dot{U}_{t+1}^\gamma)^{1/\gamma} \\ &= y_t^\rho + \beta E_t \dot{U}_{t+1}\end{aligned}\tag{S7}$$

Equation (S7) indicates the familiar expected time-additive utility specification.

APPENDIX D

PROOF OF INSTABILITY UNDER CONCAVITY OF RETURN FUNCTION

This appendix proves the instability of the optimization of dynamic CAPM under concave return functions in Chapter II.

From the recursive relation between e_t and e_{t+1} :

$$e_t = \frac{E_t[U_{t+1}^\alpha \frac{q_{t+1}y_{t+1} + A_{t+1}}{q_{t+1}y_{t+1} + A_{t+1}/(\lambda e_{t+1})}]}{E_t[U_{t+1}^\alpha]} \quad (13)$$

we can have

$$\lambda e_{t+1} < 1 \implies q_{t+1}y_{t+1} + A_{t+1}/(\lambda e_{t+1}) > q_{t+1}y_{t+1} + A_{t+1} \implies e_t < 1$$

$$\lambda e_{t+1} = 1 \implies q_{t+1}y_{t+1} + A_{t+1}/(\lambda e_{t+1}) = q_{t+1}y_{t+1} + A_{t+1} \implies e_t = 1$$

$$\lambda e_{t+1} > 1 \implies q_{t+1}y_{t+1} + A_{t+1}/(\lambda e_{t+1}) < q_{t+1}y_{t+1} + A_{t+1} \implies e_t > 1$$

Therefore we have

$$\lambda e_{t+1} > 1 \iff e_t > 1 \quad (C1)$$

Case Discussion

Case I: if $0 < \frac{A_{t+1}}{q_{t+1}y_{t+1}} \frac{1}{\lambda e_{t+1}} < 1$

define $a \equiv \frac{A_{t+1}}{q_{t+1}y_{t+1}}$, and $b \equiv \frac{1}{\lambda e_{t+1}} \implies 0 < ab < 1$

$$\begin{aligned} e_t &= \frac{E_t[U_{t+1}^\alpha \frac{1 + \frac{A_{t+1}}{q_{t+1}y_{t+1}}}{1 + \frac{A_{t+1}}{q_{t+1}y_{t+1}} \frac{1}{\lambda e_{t+1}}}] }{E_t[U_{t+1}^\alpha]} \\ &= \frac{E_t[U_{t+1}^\alpha \frac{1+a}{1+ab}]}{E_t[U_{t+1}^\alpha]} \\ &= 1 + (\frac{1}{b} - 1) \frac{E_t[U_{t+1}^\alpha \frac{ab}{1+ab}]}{E_t[U_{t+1}^\alpha]} \end{aligned}$$

by assumption of a and b , we have

$$0 < ab < 1 \implies 0 < \frac{ab}{1+ab} < 1/2 \implies 0 < \frac{E_t[U_{t+1}^\alpha \frac{ab}{1+ab}]}{E_t[U_{t+1}^\alpha]} < 1/2$$

case 1.1: if $\frac{1}{b} - 1 > 0 \iff \lambda e_{t+1} > 1 \iff e_{t+1} > 1/\lambda \implies 1 < e_t < 1 + \frac{1}{2}(\frac{1}{b} - 1) = \frac{1}{2}(1 + \lambda e_{t+1})$

case 1.2: if $\frac{1}{b} - 1 < 0 \iff \lambda e_{t+1} < 1 \iff e_{t+1} < 1/\lambda \implies 1 > e_t > 1 + \frac{1}{2}(\frac{1}{b} - 1) = \frac{1}{2}(1 + \lambda e_{t+1})$

case 1.3: if $\frac{1}{b} - 1 = 0 \iff \lambda e_{t+1} = 1 \iff e_{t+1} = 1/\lambda \implies 1 = e_t = 1 + \frac{1}{2}(\frac{1}{b} - 1) = \frac{1}{2}(1 + \lambda e_{t+1})$

Therefore

$$e_t > 1 \iff e_{t+1} > \frac{2e_t - 1}{\lambda} \quad (C2)$$

*Breakeven point $e_o = \frac{2e_o - 1}{\lambda} \implies e_o = \frac{1}{2 - \lambda} < 1$ (when $0 < \lambda < 1$)

Stability Range: $(e_o, 1)$

Case II: if $\frac{A_{t+1}}{q_{t+1}y_{t+1}} \frac{1}{\lambda e_{t+1}} > 1 \iff \frac{q_{t+1}y_{t+1}}{A_{t+1}} \lambda e_{t+1} < 1$

define $a \equiv \frac{q_{t+1}y_{t+1}}{A_{t+1}}$, and $b \equiv \lambda e_{t+1} \implies ab < 1$

$$\begin{aligned} e_t &= \frac{E_t[U_{t+1}^\alpha \frac{\frac{q_{t+1}y_{t+1}}{A_{t+1}} \lambda e_{t+1} + \lambda e_{t+1}}{\frac{q_{t+1}y_{t+1}}{A_{t+1}} \lambda e_{t+1} + 1}]}{E_t[U_{t+1}^\alpha]} \\ &= \frac{E_t[U_{t+1}^\alpha \frac{(1+a)b}{1+ab}]}{E_t[U_{t+1}^\alpha]} \\ &= b + (1-b) \frac{E_t[U_{t+1}^\alpha \frac{ab}{1+ab}]}{E_t[U_{t+1}^\alpha]} \end{aligned}$$

by assumption of a and b , we have

$$0 < ab < 1 \implies 0 < \frac{ab}{1+ab} < 1/2 \implies 0 < \frac{E_t[U_{t+1}^\alpha \frac{ab}{1+ab}]}{E_t[U_{t+1}^\alpha]} < 1/2$$

case 2.1: if $1 - b < 0 \iff \lambda e_{t+1} > 1 \iff e_{t+1} > 1/\lambda \implies b > e_t > b + \frac{1}{2}(1 - b) = \frac{1}{2}(1 + \lambda e_{t+1})$

case 2.2: if $1 - b > 0 \iff \lambda e_{t+1} < 1 \iff e_{t+1} < 1/\lambda \implies b < e_t < b + \frac{1}{2}(1 - b) = \frac{1}{2}(1 + \lambda e_{t+1})$

case 2.3: if $1 - b = 0 \iff \lambda e_{t+1} = 1 \iff e_{t+1} = 1/\lambda \implies b = e_t =$
 $b + \frac{1}{2}(1 - b) = \frac{1}{2}(1 + \lambda e_{t+1})$

Therefore

$$e_t > 1 \implies \frac{2e_t - 1}{\lambda} > e_{t+1} > \frac{e_t}{\lambda} \quad (\text{C3})$$

*Breakeven point $e_o = \frac{2e_o - 1}{\lambda} \implies e_o = \frac{1}{2 - \lambda} < 1$ (when $0 < \lambda < 1$)

Stability Range: $(0.5, e_o]$

Case III: if $\frac{A_{t+1}}{q_{t+1}y_{t+1}} \frac{1}{\lambda e_{t+1}} = 1 \iff q_{t+1}y_{t+1}\lambda e_{t+1} = A_{t+1}$

$$\begin{aligned} e_t &= \frac{1 + \lambda e_{t+1}}{2} \\ \implies e_{t+1} &= \frac{2e_t - 1}{\lambda} \end{aligned} \quad (\text{C4})$$

Summarize C2, C3, and C4, we have for all cases

$$e_t > 1 \implies e_{t+1} > \frac{e_t}{\lambda} \quad (\text{C5})$$

APPENDIX E

ZERO ONE SIMULATION OF THE AR REPRESENTATION

This appendix shows the zero one simulation of AR representation in Chapter III.

$$\begin{aligned}
 FE_{t+1} &= \Theta_0 \epsilon_{t+1} = \begin{bmatrix} \theta_{110} & \theta_{120} & \theta_{130} \\ \theta_{210} & \theta_{220} & \theta_{230} \\ \theta_{310} & \theta_{320} & \theta_{330} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t+1} \\ \epsilon_{2,t+1} \\ \epsilon_{3,t+1} \end{bmatrix} \\
 &= \begin{bmatrix} \theta_{110}\epsilon_{1,t+1} + \theta_{120}\epsilon_{2,t+1} + \theta_{130}\epsilon_{3,t+1} \\ \theta_{210}\epsilon_{1,t+1} + \theta_{220}\epsilon_{2,t+1} + \theta_{230}\epsilon_{3,t+1} \\ \theta_{310}\epsilon_{1,t+1} + \theta_{320}\epsilon_{2,t+1} + \theta_{330}\epsilon_{3,t+1} \end{bmatrix} \\
 &= \begin{bmatrix} 1 & 0 & 0 \\ \zeta & -(a_3 + b_3 Z_t) & Y_t \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \epsilon_{1,t+1} \\ \epsilon_{2,t+1} \\ \epsilon_{3,t+1} \end{bmatrix} = \begin{bmatrix} \epsilon_{1,t+1} \\ \zeta\epsilon_{1,t+1} - (a_3 + b_3 Z_t)\epsilon_{2,t+1} + Y_t\epsilon_{3,t+1} \\ \epsilon_{3,t+1} \end{bmatrix}
 \end{aligned}$$

$$\begin{aligned}
 FE_{t+2} &= \Theta_0 \epsilon_{t+2} + \Theta_1 \epsilon_{t+1} \\
 &= \begin{bmatrix} \theta_{110} & \theta_{120} & \theta_{130} \\ \theta_{210} & \theta_{220} & \theta_{230} \\ \theta_{310} & \theta_{320} & \theta_{330} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t+2} \\ \epsilon_{2,t+2} \\ \epsilon_{3,t+2} \end{bmatrix} + \begin{bmatrix} \theta_{111} & \theta_{121} & \theta_{131} \\ \theta_{211} & \theta_{221} & \theta_{231} \\ \theta_{311} & \theta_{321} & \theta_{331} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t+1} \\ \epsilon_{2,t+1} \\ \epsilon_{3,t+1} \end{bmatrix} \\
 &= \begin{bmatrix} \epsilon_{1,t+2} \\ \zeta\epsilon_{1,t+2} - (a_3 + b_3 Z_t)\epsilon_{2,t+2} + Y_t\epsilon_{3,t+2} \\ \epsilon_{3,t+2} \end{bmatrix} \\
 &+ \begin{bmatrix} b_1 & 0 & 0 \\ \zeta b_1 + (a_3 + b_3 Z_t)\zeta & -(a_3 + b_3 Z_t)^2 & (a_3 + b_3 Z_t + b_3)Y_t \\ 0 & 0 & b_3 \end{bmatrix} \begin{bmatrix} \epsilon_{1,t+1} \\ \epsilon_{2,t+1} \\ \epsilon_{3,t+1} \end{bmatrix} \\
 &= \begin{bmatrix} \epsilon_{1,t+2} \\ \zeta\epsilon_{1,t+2} - (a_3 + b_3 Z_t)\epsilon_{2,t+2} + Y_t\epsilon_{3,t+2} \\ \epsilon_{3,t+2} \end{bmatrix} \\
 &+ \begin{bmatrix} b_1\epsilon_{1,t+1} \\ [\zeta b_1 + (a_3 + b_3 Z_t)\zeta]\epsilon_{1,t+1} - (a_3 + b_3 Z_t)^2\epsilon_{2,t+1} + (a_3 + b_3 Z_t + b_3)Y_t\epsilon_{3,t+1} \\ b_3\epsilon_{3,t+1} \end{bmatrix}
 \end{aligned}$$

$$\begin{aligned}
FE_{t+3} &= \Theta_0 \epsilon_{t+3} + \Theta_1 \epsilon_{t+2} + \Theta_2 \epsilon_{t+1} \\
&= \begin{bmatrix} \theta_{110} & \theta_{120} & \theta_{130} \\ \theta_{210} & \theta_{220} & \theta_{230} \\ \theta_{310} & \theta_{320} & \theta_{330} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t+3} \\ \epsilon_{2,t+3} \\ \epsilon_{3,t+3} \end{bmatrix} + \begin{bmatrix} \theta_{111} & \theta_{121} & \theta_{131} \\ \theta_{211} & \theta_{221} & \theta_{231} \\ \theta_{311} & \theta_{321} & \theta_{331} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t+2} \\ \epsilon_{2,t+2} \\ \epsilon_{3,t+2} \end{bmatrix} + \begin{bmatrix} \theta_{112} & \theta_{122} & \theta_{132} \\ \theta_{212} & \theta_{222} & \theta_{232} \\ \theta_{312} & \theta_{322} & \theta_{332} \end{bmatrix} \begin{bmatrix} \epsilon_{1,t+1} \\ \epsilon_{2,t+1} \\ \epsilon_{3,t+1} \end{bmatrix} \\
&= \begin{bmatrix} \epsilon_{1,t+3} \\ \zeta \epsilon_{1,t+3} - (a_3 + b_3 Z_t) \epsilon_{2,t+3} + Y_t \epsilon_{3,t+3} \\ \epsilon_{3,t+3} \end{bmatrix} \\
&+ \begin{bmatrix} b_1 \epsilon_{1,t+2} \\ [\zeta b_1 + (a_3 + b_3 Z_t) \zeta] \epsilon_{1,t+2} - (a_3 + b_3 Z_t)^2 \epsilon_{2,t+2} + (a_3 + b_3 Z_t + b_3) Y_t \epsilon_{3,t+2} \\ b_3 \epsilon_{3,t+2} \end{bmatrix} \\
&+ \begin{bmatrix} b_1^2 & 0 & 0 \\ \zeta b_1^2 + (a_3 + b_3 Z_t)(b_1 + a_3 + b_3 Z_t) \zeta & -(a_3 + b_3 Z_t)^3 & (a_3 + b_3 Z_t)(a_3 + b_3 Z_t + b_3) Y_t + b_3^2 Y_t \\ 0 & 0 & b_3^2 \end{bmatrix} \begin{bmatrix} \epsilon_{1,t+1} \\ \epsilon_{2,t+1} \\ \epsilon_{3,t+1} \end{bmatrix} \\
&= \begin{bmatrix} \epsilon_{1,t+3} \\ \zeta \epsilon_{1,t+3} - (a_3 + b_3 Z_t) \epsilon_{2,t+3} + Y_t \epsilon_{3,t+3} \\ \epsilon_{3,t+3} \end{bmatrix} \\
&+ \begin{bmatrix} b_1 \epsilon_{1,t+2} \\ [\zeta b_1 + (a_3 + b_3 Z_t) \zeta] \epsilon_{1,t+2} - (a_3 + b_3 Z_t)^2 \epsilon_{2,t+2} + (a_3 + b_3 Z_t + b_3) Y_t \epsilon_{3,t+2} \\ b_3 \epsilon_{3,t+2} \end{bmatrix} \\
&+ \begin{bmatrix} b_1^2 \epsilon_{1,t+1} \\ [\zeta b_1^2 + (a_3 + b_3 Z_t)(b_1 + a_3 + b_3 Z_t) \zeta] \epsilon_{1,t+1} - (a_3 + b_3 Z_t)^3 \epsilon_{2,t+1} + [(a_3 + b_3 Z_t)(a_3 + b_3 Z_t + b_3) Y_t + b_3^2 Y_t] \epsilon_{3,t+1} \\ b_3^2 \epsilon_{3,t+1} \end{bmatrix}
\end{aligned}$$

APPENDIX F

FORECAST ERROR DECOMPOSITION FOR Y_{t+1}

This appendix shows the forecast error decomposition for Y_{t+1} in Chapter III.

$$\begin{aligned} Var(\text{FE}_{t+1}(Y_{t+1})) &= [\zeta(1 - a_3 - b_3 Z_t)]^2 \sigma_1^2 \\ &\quad + (a_3 + b_3 Z_t)^4 \sigma_2^2 + [(1 - a_3 - b_3 Z_t)Y_t]^2 \sigma_3^2 + (a_3 + b_3 Z_t)^2 \sigma_2^2 \sigma_3^2 + \\ &\quad 2[\zeta(1 - a_3 - b_3 Z_t)^2 Y_t] \rho_{13} \sigma_1 \sigma_3 \end{aligned}$$

$$\begin{aligned} \text{FE}_{t+2}(Y_{t+2}) &= \zeta \epsilon_{1,t+2} - (a_3 + b_3 Z_t) \epsilon_{2,t+2} + Y_t \epsilon_{3,t+2} \\ &\quad + [\zeta b_1 + (a_3 + b_3 Z_t) \zeta] \epsilon_{1,t+1} - (a_3 + b_3 Z_t)^2 \epsilon_{2,t+1} \\ &\quad + (a_3 + b_3 Z_t + b_3) Y_t \epsilon_{3,t+1} \\ &= \zeta \epsilon_{1,t+2} - (a_3 + b_3 Z_t) (\zeta \epsilon_{1,t+2} + Y_t \epsilon_{3,t+2} - U_{2,t+2} a_3 - U_{2,t+2} b_3 Z_t - U_{2,t+2} \epsilon_{3,t+2}) \\ &\quad + Y_t \epsilon_{3,t+2} + [\zeta b_1 + (a_3 + b_3 Z_t) \zeta] \epsilon_{1,t+1} - (a_3 + b_3 Z_t)^2 (\zeta \epsilon_{1,t+1} \\ &\quad + Y_t \epsilon_{3,t+1} - U_{2,t+1} a_3 - U_{2,t+1} b_3 Z_t - U_{2,t+1} \epsilon_{3,t+1}) \\ &\quad + (a_3 + b_3 Z_t + b_3) Y_t \epsilon_{3,t+1} \\ &= \zeta \epsilon_{1,t+2} (1 - a_3 - b_3 Z_t) + (a_3 + b_3 Z_t)^2 U_{2,t+2} + (1 - a_3 - b_3 Z_t) Y_t \epsilon_{3,t+2} \\ &\quad + (a_3 + b_3 Z_t) U_{2,t+2} \epsilon_{3,t+2} + [\zeta b_1 + (a_3 + b_3 Z_t) \zeta - (a_3 + b_3 Z_t)^2 \zeta] \epsilon_{1,t+1} \\ &\quad + (a_3 + b_3 Z_t)^3 U_{2,t+1} + [a_3 + b_3 Z_t + b_3 - (a_3 + b_3 Z_t)^2] Y_t \epsilon_{3,t+1} \\ &\quad + (a_3 + b_3 Z_t)^2 U_{2,t+1} \epsilon_{3,t+1} \end{aligned}$$

$$\begin{aligned} Var(\text{FE}_{t+2}(Y_{t+2})) &= \{[1 - a_3 - b_3 Z_t]^2 + [b_1 + (a_3 + b_3 Z_t) - (a_3 + b_3 Z_t)^2]^2\} \zeta^2 \sigma_1^2 \\ &\quad + [(a_3 + b_3 Z_t)^4 + (a_3 + b_3 Z_t)^6] \sigma_2^2 + \{[1 - a_3 - b_3 Z_t]^2 + [a_3 + b_3 Z_t + \\ &\quad b_3 - (a_3 + b_3 Z_t)^2]^2\} Y_t^2 \sigma_3^2 + [(a_3 + b_3 Z_t)^2 + (a_3 + b_3 Z_t)^4] \sigma_2^2 \sigma_3^2 + \\ &\quad 2\{(1 - a_3 - b_3 Z_t)^2 + [b_1 + (a_3 + b_3 Z_t) - (a_3 + b_3 Z_t)^2][a_3 + b_3 Z_t + \\ &\quad b_3 - (a_3 + b_3 Z_t)^2]\} \zeta Y_t \rho_{13} \sigma_1 \sigma_3 \end{aligned}$$

$$\begin{aligned} \text{FE}_{t+3}(Y_{t+3}) &= \zeta \epsilon_{1,t+3} - (a_3 + b_3 Z_t) \epsilon_{2,t+3} + Y_t \epsilon_{3,t+3} \\ &\quad + [\zeta b_1 + (a_3 + b_3 Z_t) \zeta] \epsilon_{1,t+2} - (a_3 + b_3 Z_t)^2 \epsilon_{2,t+2} \\ &\quad + (a_3 + b_3 Z_t + b_3) Y_t \epsilon_{3,t+2} \\ &\quad + [\zeta b_1^2 + (a_3 + b_3 Z_t)(b_1 + a_3 + b_3 Z_t) \zeta] \epsilon_{1,t+1} - (a_3 + b_3 Z_t)^3 \epsilon_{2,t+1} \\ &\quad + [(a_3 + b_3 Z_t)(a_3 + b_3 Z_t + b_3) Y_t + b_3^2 Y_t] \epsilon_{3,t+1} \end{aligned}$$

$$\begin{aligned}
&= \zeta \epsilon_{1,t+3} - (a_3 + b_3 Z_t) (\zeta \epsilon_{1,t+3} + Y_t \epsilon_{3,t+3} - U_{2,t+3} a_3 - U_{2,t+3} b_3 Z_t - U_{2,t+3} \epsilon_{3,t+3}) \\
&\quad + Y_t \epsilon_{3,t+3} \\
&\quad + [\zeta b_1 + (a_3 + b_3 Z_t) \zeta] \epsilon_{1,t+2} - (a_3 + b_3 Z_t)^2 (\zeta \epsilon_{1,t+2} \\
&\quad + Y_t \epsilon_{3,t+2} - U_{2,t+2} a_3 - U_{2,t+2} b_3 Z_t - U_{2,t+2} \epsilon_{3,t+2}) \\
&\quad + (a_3 + b_3 Z_t + b_3) Y_t \epsilon_{3,t+2} \\
&\quad + [\zeta b_1^2 + (a_3 + b_3 Z_t) (b_1 + a_3 + b_3 Z_t) \zeta] \epsilon_{1,t+1} - (a_3 + b_3 Z_t)^3 (\zeta \epsilon_{1,t+1} \\
&\quad + Y_t \epsilon_{3,t+1} - U_{2,t+1} a_3 - U_{2,t+1} b_3 Z_t - U_{2,t+1} \epsilon_{3,t+1}) \\
&\quad + [(a_3 + b_3 Z_t) (a_3 + b_3 Z_t + b_3) Y_t + b_3^2 Y_t] \epsilon_{3,t+1} \\
&= \zeta \epsilon_{1,t+3} (1 - a_3 - b_3 Z_t) + (a_3 + b_3 Z_t)^2 U_{2,t+3} + (1 - a_3 - b_3 Z_t) Y_t \epsilon_{3,t+3} \\
&\quad + (a_3 + b_3 Z_t) U_{2,t+3} \epsilon_{3,t+3} + [\zeta b_1 + (a_3 + b_3 Z_t) \zeta - (a_3 + b_3 Z_t)^2 \zeta] \epsilon_{1,t+2} \\
&\quad + (a_3 + b_3 Z_t)^3 U_{2,t+2} + [a_3 + b_3 Z_t + b_3 - (a_3 + b_3 Z_t)^2] Y_t \epsilon_{3,t+2} \\
&\quad + (a_3 + b_3 Z_t)^2 U_{2,t+2} \epsilon_{3,t+2} \\
&\quad + [\zeta b_1^2 + (a_3 + b_3 Z_t) (b_1 + a_3 + b_3 Z_t) \zeta - (a_3 + b_3 Z_t)^3 \zeta] \epsilon_{1,t+1} \\
&\quad + (a_3 + b_3 Z_t)^4 U_{2,t+1} \\
&\quad + [(a_3 + b_3 Z_t) (a_3 + b_3 Z_t + b_3) + b_3^2 - (a_3 + b_3 Z_t)^3] Y_t \epsilon_{3,t+1} \\
&\quad + (a_3 + b_3 Z_t)^3 U_{2,t+1} \epsilon_{3,t+1}
\end{aligned}$$

$$\begin{aligned}
&Var(\text{FE}_{t+3}(Y_{t+3})) \\
&= \{[1 - a_3 - b_3 Z_t]^2 + [b_1 + (a_3 + b_3 Z_t) - (a_3 + b_3 Z_t)^2]^2 \\
&\quad + [b_1^2 + (a_3 + b_3 Z_t) (b_1 + a_3 + b_3 Z_t) - (a_3 + b_3 Z_t)^3]^2\} \zeta^2 \sigma_1^2 \\
&\quad + [(a_3 + b_3 Z_t)^4 + (a_3 + b_3 Z_t)^6 + (a_3 + b_3 Z_t)^8] \sigma_2^2 \\
&\quad + \{[1 - a_3 - b_3 Z_t]^2 + [a_3 + b_3 Z_t + b_3 - (a_3 + b_3 Z_t)^2]^2 \\
&\quad + [(a_3 + b_3 Z_t) (a_3 + b_3 Z_t + b_3) + b_3^2 - (a_3 + b_3 Z_t)^3]^2\} Y_t^2 \sigma_3^2 \\
&\quad + [(a_3 + b_3 Z_t)^2 + (a_3 + b_3 Z_t)^4 + (a_3 + b_3 Z_t)^6] \sigma_2^2 \sigma_3^2 \\
&\quad + 2\{(1 - a_3 - b_3 Z_t)^2 \\
&\quad + [b_1 + (a_3 + b_3 Z_t) - (a_3 + b_3 Z_t)^2][a_3 + b_3 Z_t + b_3 - (a_3 + b_3 Z_t)^2] \\
&\quad + [b_1^2 \\
&\quad + (a_3 + b_3 Z_t) (b_1 + a_3 + b_3 Z_t) - (a_3 + b_3 Z_t)^3][(a_3 + b_3 Z_t) (a_3 + b_3 Z_t \\
&\quad + b_3) + b_3^2 - (a_3 + b_3 Z_t)^3]\} \zeta Y_t \rho_{13} \sigma_1 \sigma_3
\end{aligned}$$

APPENDIX G

R SCRIPT CODE FOR SMOOTH COEFFICIENT ESTIMATION OF PANEL

MODEL

This appendix shows the R script code for smooth coefficient estimation of panel model in Chapter IV.

```
# install packages 'np' and 'nplplot' from menu
# load packages 'np' and 'nplplot' from menu

# set working dir
setwd("C:/Users/jxu/Desktop/New folder (2)")
getwd()
# import data
panel=read.table('PanelData05.txt', header = TRUE)
panel

#plot data # save as emf file or 100% JPG file
coplot(GP ~ year|state, type="l", data=panel) # Lines
coplot(Rain ~ year|state, type="l", data=panel) # Lines
coplot(Temp ~ year|state, type="l", data=panel) # Lines
coplot(y ~ year|state, type="l", data=panel) # Lines
coplot(x ~ year|state, type="l", data=panel) # Lines

#scoef
model.scoef <- npscoef(y ~ x| GP, betas = TRUE,errors = TRUE, data = panel)
model.scoef <- npscoef(y ~ x| Temp, betas = TRUE,errors = TRUE, data = panel)
model.scoef <- npscoef(y ~ x| Rain, betas = TRUE,errors = TRUE, data = panel)
summary(model.scoef)
colMeans(coef(model.scoef))
#plot(model.scoef)

#bw <- npscoefbw(formula=y~x|GP, data = panel)
#bw <- npscoefbw(formula=y~x|Temp, data = panel)
bw <- npscoefbw(formula=y~x|Rain, data = panel)
#summary(bw)

plot(bw, theta=-295, phi=10)
plot(bw, theta=-235, phi=10)
plot(bw, theta=-175, phi=10)
```

```

plot(bw, theta=-115, phi=10)
plot(bw, theta=-55, phi=10)
plot(bw, theta=5, phi=10)

#scoef_intercept_GP <- coef(model.scoef)[,1]
#scoef_intercept_Temp <- coef(model.scoef)[,1]
scoef_intercept_Rain <- coef(model.scoef)[,1]

#coplot(scoef_intercept_GP~year|state, type="l", data=panel) # Lines
#coplot(scoef_intercept_Temp~year|state, type="l", data=panel) # Lines
coplot(scoef_intercept_Rain~year|state, type="l", data=panel) # Lines

# We could manually plot fitted values and error bounds as follows:
upper <- predict(model.scoef)+2*se(model.scoef)
lower <- predict(model.scoef)-2*se(model.scoef)
#plot(y~x)
coplot(y~x|state, data = panel)
#lines (predict(model.scoef)~x|state, type="l", data = panel)
# lines (upper~x, lty=2,col="red", type="l", data = panel)
# lines (lower~x, lty=2,col="red", type="l", data = panel)

#write.csv(scoef_intercept_GP,file = "gp.txt")
#write.csv(scoef_intercept_Temp,file = "temp.txt")
write.csv(scoef_intercept_Rain,file = "rain.txt")

```

Note: The above code refers to

R Graphical Manual, Smooth Coefficient Kernel Regression, at website
http://rgm3.lab.nig.ac.jp/RGM/r_function?p=np&f=np.smoothcoef

R-Package-np / man / np.smoothcoef.Rd, at website <https://github.com/JeffreyRacine/R-Package-np/blob/master/man/np.smoothcoef.Rd>

Hayfield, T., & Racine, J. S., 2007. “Nonparametric Kernel Smoothing Methods for Mixed Datatypes”. R Package Version 0.13-1.

Hayfield, T., and Racine, J. S., 2008. “Nonparametric Econometrics: The NP Package.” *Journal of Statistical Software* 27(5):1-32.

Racine, J. S., 2009. “Nonparametric and Semiparametric Methods in R.” *Advances in Econometrics* 25:335-375.