THREE ESSAYS ON FARMLAND INVESTMENT

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Ashraf Noumir

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THE PURDUE UNIVERSITY GRADUATE SCHOOL
STATEMENT OF COMMITTEE APPROVAL

Dr. Michael Langemeier

Department of Agricultural Economics

Dr. Gerald Shively

Department of Agricultural Economics

Dr. Michael Wetzstein

Department of Agricultural Economics

Dr. Mindy Mallory

Department of Agricultural Economics

Dr. Frederi Viens

Department of Statistics and Probability, Michigan State University

Approved by:

Dr. Nicole J. Olynk Widmar

To the soul of my mother. Nothing of this would be possible without your effort and dedication raising me up.

To my father and my brother. Your support and encouragement inspired me to pursue this journey

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LIST OF ABBERVIATIONS

CAPM	Capital Asset Pricing Model
CRSP	Center for Research and Security Prices
Conditional CAPM	Conditional Capital Asset Pricing Model
CAPE	Cyclically Adjusted Price Earnings Ratio
FRED	Federal Reserve Economic Data
GMM	Generalized Method of Moments
Min Var Portfolio	Minimum -Variance Portfolio
NCREIF	National Council of Real Estate Investment Fiduciaries
ITAA-CREF	Teachers Insurance and Annuity Association-College Retirement Equities Fund

ABSTRACT

This dissertation is comprised of three essays focusing on farmland economics with particular attention to characterizing risk and return of farmland investment. The first essay in chapter two discusses the portfolio performance of different farmland qualities in different geographic regions in two Corn Belt states, namely Indiana and Iowa. I found that risk of different farmland qualities in different geographic regions are low compared to other assets. Excess return, however, is higher and statistically significant in Indiana relative to Iowa. Results also suggest that diversifying across farmland locations and qualities contributes positively to farmland investment in Indiana but not in Iowa.

The second essay in chapter three examines whether farmland has a risk factor in asset pricing models. In other words, I examine whether the additional return of farmland investment is associated with additional risk. Relying on the National Council of Real Estate Investment Fiduciaries (NCREIF) farmland property index and U.S. stock returns, I show that exposure to farmland risk has neither economical nor statistical explanatory power for the expected stock returns across a range of equity portfolios.

In the third essay in chapter four, I develop a decision rule to determine the optimal mix of owned and rented farmland operated by a farmer or agricultural investor. I do so by extending portfolio theory to get the optimal mix of owned and rented farmland that minimize farming risk. Utilizing data on West Central Indiana, this portfolio rule shows that owning is far more attractive than renting farmland. Chapter five concludes the three essays.

CHAPTER 1. INTRODUCTION

As appears in the title, the principal focus of this dissertation is on farmland investment. Farmland is the most dominant and important agricultural asset. It represents over 80 percent of total asset value on the U.S. farm balance sheet (Burns et al, 2018). Coupled with this, there was a surge in U.S. farmland values over the past two decades. As a result, farmland attracts a great deal of interest from researchers and practitioners alike. For example, since 2007, institutional investors allocated $30 to $40 billion to global farmland (Fairbairn, 2014). This interest involves but is not limited to pricing and management of farmland investment. This dissertation is related to these two broad topics with two essays related to farmland pricing and one essay related to farmland management.

The first and second essays contribute to the asset pricing and portfolio choice of farmland. Farmland is seen as a capital asset, like stocks, bonds, and real estate, whose return is uncertain. Given this uncertainty / risk of future stream of farmland return, how does farmland compare to other capital assets. In the first essay, I examine the risk/return characteristics of farmland and how farmland fits into a portfolio composed of other traditional capital assets like stocks and bonds. Many studies have contributed to this strand. The unique contribution of this essay is, however, the examination of different land qualities in different geographic regions. The main motivation for this essay is that aggregation of farmland qualities in previous literature may mask or fail to capture the heterogeneous quality features of farmland. More specifically, the difference between poor, average and good farmland qualities may be lost in this aggregation. Therefore, instead of only diversifying along the geographic dimension, I add the quality dimension to the geographic dimension. As more detailed farmland quality data are made available in two Corn Belt States, namely Indiana and Iowa, I relied on their data to figure out whether there are additional diversification benefits by diversifying across farmland qualities. I found that the betas (risk) of different farmland qualities for different regions in Indiana and Iowa are all around zero which indicate the low farmland investment risk compared to other assets (i.e., farmland adds very little risk to the well diversified portfolio). Looking at different farmland qualities in different regions in Indiana and Iowa, I found mixed results on the portfolio performance of adding quality diversification to geographic diversification of farmland investments. In particular, adding a quality dimension to the geographic dimension provided significant improvement in the reward-to-risk ratio in Indiana farmland, but not for Iowa farmland.

The second essay digs deeper into asset pricing and portfolio performance of farmland. Motivated by the well-documented presence of real estate risk factor and real estate factor premium (i.e., the extra return of real estate investing is associated with extra risk) along with the similar investment performance of farmland and real estate, the second essay examines whether or not farmland also has a factor premium. Therefore, I examine whether farmland has factor risk to which exposure is necessary to gain a higher return. The primary finding in this essay is that, unlike real estate, farmland has no risk factor and consequently no risk premium. The relatively high abnormal return for farmland is not explained by risk models. Put differently, my findings suggest that even though farmland has a high risk-adjusted return relative to the market portfolio, there is no risk relationship between farmland and stock returns.

The third essay contributes to the effective management of farmland by focusing on developing a decision rule that helps farmers and / or agricultural investors with their land tenure decisions. In particular, we model the mixed-tenure strategy that involves owning part of farmland and renting the other part. In fact, mixed-tenure farmlands have increased dramatically during the last several years. In order to analyze this phenomenon, I employ a portfolio perspective to model this optimal land tenure decision. My approach involves examining the mixture of rented and owned land as a portfolio of operating income and capital gain. I formulated the problem as a portfolio selection model with two risky assets. The first asset is owned farmland whose return consists of operating income and capital gains. The second asset is rented farmland, for which operating income is the only source of net returns. Applying this model to farmland in west central Indiana yielded results that are in favor of owning, rather than renting, farmland.

CHAPTER 2. RISK AND RETURN OF DIFFERENTIATED FARMLAND LOCATIONS/QUALITIES

Abstract

Using data on farmland values in Indiana and Iowa, this chapter examines the risk and return characteristics surrounding top, medium, and poor farmland qualities in different locations in these two states. I find that systematic risks of locations/qualities are very low (indistinguishable from 0). In terms of risk-adjusted return, results show that Indiana farmland has more excess return and higher reward-to-risk ratios than Iowa. Also, adding the quality dimension to the geographic dimension in portfolio selection strategies improved the portfolio reward-to-risk ratio for Indiana but not for Iowa.

Keywords: Farmland, farmland quality, minimum variance (Min Var) portfolio, reward-to-risk ratio, Capital Asset Pricing Model (CAPM).

2.1 Introduction

Farmland represents more than 80% of the aggregate U.S. farm balance sheet (Burns *et al.*, 2018). Being the dominant agricultural asset coupled with the recent surge in farmland prices has encouraged practitioners and researchers to conduct economic and investment analysis of farmland as an asset class like other traditional asset classes (i.e., stocks and bonds). Favorable investment features of farmland investment highlighted in the literature include, but are not limited to, higher return compared to other non-agricultural assets, low systematic risk (β), low correlation with other traditional asset classes, and a hedge against inflation (Baker *et al.*, 2014; Barry, 1980; Irwin *et* *al*.,1988; Bjorson and Innes, 1992). In almost all of these studies, farmland data were either at the national or regional levels, or did not account for differentiated land quality. Therefore, the main aim of this chapter is to decompose the farmland performance into the performance of different farmland qualities in different geographical regions. Specifically, I revisit the asset pricing and portfolio selection models used in previous studies to explore the portfolio performance of farmland locations/qualities.

The typical criteria used to differentiate farmland quality is soil quality. Two Corn Belt states are considered: Indiana and Iowa. I investigate whether the above features of farmland investment still hold when we decompose farmland into three quality levels (poor, average, and top) for different regions in these states. I estimate the return, volatility, and the systematic risk (β) of each of the different locations/qualities of farmland in the two states. In this regard, I take advantage of two farmland surveys published in Indiana and Iowa that show cash rent and farmland values for each location/quality in Indiana and Iowa. Also, I use a portfolio approach to farmland investment with two dimensions, geographic location and quality. Using each farmland quality/location category as an asset class, I determine the optimal portfolios composed of different weights for these asset classes. The general approach is similar to Lins *et al*. (1992) who examined the geographic diversification of farmland across twenty-eight U.S. states. I extend their work by incorporating the farmland quality dimension to the location dimension and forming the portfolio of farmland based on these two dimensions. Also, the geographic location in Lins *et al*. (1992) is defined by state while my geographic location is defined by regions within states. My motive for using a portfolio approach for farmland investment is to enable investors to garner better insights pertaining to farmland investment. It is not uncommon for institutional investors to have asset specific managers where each manager manages his asset classes independently from other assets held by the institutional investor. In addition to my portfolio analysis, I use the Capital Asset pricing model (CAPM) to examine the performance of each land location/quality when added to a diversified portfolio of other assets.

In a nutshell, this chapter provides an answer the following question: *what is the portfolio performance of differentiated farmland locations/qualities*? By answering this question, I provide a significant contribution to the farmland investment literature by paving the path for examining the portfolio performance of heterogeneous farmland (i.e., quality and location heterogeneity).

My findings show that systematic risks of locations/qualities in Indiana and Iowa are indistinguishable from 0. This result is shared by the general literature on risk and return of farmland. In terms of risk-adjusted return, my results show that Indiana farmland has more excess return and higher reward-to-risk ratios (farmland return divided by the standard deviation of this return) than Iowa. Also, adding a quality dimension to the geographic dimension in portfolio selection strategies showed mixed results: it improved the portfolios' reward-to-risk ratio for Indiana, but not for Iowa. What is interesting is that the three farmland quality levels (poor, average, top) are selected in the portfolios with dominant weight for the average quality farmland.

2.2 Literature Review

This chapter is related to two main strands of literature. The first one involves studies examining the relationship between soil quality and farmland prices and /or returns. Intuitively, the better the soil quality, the higher the farmland price and net return per acre. However, I argue that this does not necessarily imply that the better the soil quality, the better the diversification potential. The second strand is the portfolio selection and asset pricing studies that investigate the investment performance of farmland relative to other assets, such as stocks and bonds.

2.2.1 Land Value and Soil Quality

Several studies have investigated the relationship between farmland characteristics and values. One of the characteristics that is relatively common among previous studies is soil characteristics. Indeed, soil characteristics are intuitively expected to have an important role in farmland productivity and farmland value. Empirical evidence mostly substantiates this relationship. Miranowski and Hammes (1984) attempted to address whether soil characteristics are capitalized into farmland value. Using both transaction and survey data, they found that three measures of soil characteristics (top soil depth, RKLS, and PH[1]) have a statistically and economically significant effect on farmland value in Iowa. Similar results were found by Gardner and Barrows (1985).

Miranowski and Hammes (1984) and Gardner and Barrows (1985) motivated a line of literature examining the impact of improvements in farmland characteristics on its value. In this vein, the findings are mixed. Palquist and Danielson (1989) used a hedonic model to examine the impact of erosion control and drainage on land value in North Carolina. Their findings indicate that improving soil quality is an important determinant of farmland price, however, its effect is radically reduced in farmland that is subject to urban conversion. Ervin and Mill (1985) showed that erosion control has mixed effects on farmland prices. They concluded that farmland markets can succeed in transmitting the appropriate signals on the soil erosion effect given that this information is available.

Other recent studies confirmed the role of soil quality on farmland value. For example, Nickerson et al. (2012) found a strong positive correlation between farmland values and soil quality in Corn Belt, Lake States, and North Dakota, a negative relationship between farmland and

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[1] RKLS is a measure of the potential soil erosion and PH is a measure soil acidity.

soil quality in the Appalachian region. Sklenicka et al. (2013) show that the one of the key factors affecting farmland prices in the Czech Republic is soil quality. Ma and Swinton (2012) applied the hedonic method to value farmland in Southwestern Michigan using both appraisal and transaction data. Their results suggest that there is significant emphasis on the soil quality in the appraisal of farmland values. This study will contribute to the above strand of literature by looking at the portfolio performance, as opposed to the individual performance of different farmland qualities.

2.2.2 Portfolio of Farmland and Other Assets

Over the last three decades, farmland has been regarded as an attractive asset class to non-agricultural investors, particularly institutional investors. Thus, a lot of academic interest has been directed toward assessing the risk and return of farmland. This is primarily done by applying asset pricing and portfolio theory to farmland investment. The farmland portfolio selection literature involves two lines of thought.

The first one involves "independent" farmland diversification. By independent I mean forming a portfolio of only one asset class which in this case is farmland, irrespective of other asset classes. This involves studies that looked at geographic diversification of farmland. For example, Lins *et al*. (1992) formed a farmland portfolio based on farmland in 28 states. Hardin and Cheng (2002) conducted a formal test of whether there was a significant difference between portfolio performance of a farmland portfolio formed based on the mean-variance rule compared to the naïve equal weighted geographic allocation rule. Their results suggested that there is no significant difference between the two allocation methods.

The second line of thought examines the portfolio performance of the traditional asset classes when farmland is added to the portfolio (e.g., Hardin and Cheng, 2002; Lins *et al*., 1992;

Kuethe *et al* 2013). The common finding of these studies is the existence of diversification benefits when farmland is added to a portfolio containing traditional assets, such as stocks and bonds. For example, Kuethe et al. (2013) examined the risk and return characteristics of farmland after the 2008 financial crisis. They did so by comparing the risk and return characteristics of farmland with that of gold, three-month treasury bills, the Dow Jones Industrial Average index, and the Standard & Poor's S&P 500 index. Their findings suggest that farmland has a higher average return and lower volatility compared to these other investment alternatives. Lins et al (1992) found that adding farmland to a portfolio composed of stocks, bonds, and real estate significantly improves the diversification performance or the risk-return characteristics of the new portfolio.

2.3 Methodology

My primary goal is to investigate whether the previously mentioned favorable investment features of farmland still hold when we use different land qualities. The Mean-Variance (MV) portfolio selection model will be applied to a portfolio of different farmland qualities in different geographic regions. Given a required mean return k, a typical M-V model is as follows:

$$\min_{X} \boldsymbol{X}^{`}\,\Omega\,\boldsymbol{X} \qquad (1)$$

$$S.T\ \ \boldsymbol{X}^{`}\boldsymbol{1} = 1. \qquad (2)$$

$$\boldsymbol{C}^{`}\boldsymbol{X} = k. \qquad (3)$$

where $\boldsymbol{X}$ is the vector of asset weights, Ω is the covariance matrix of the returns of the assets considered, and $\boldsymbol{C}^{`}$ is the transpose of the vector of mean return of each asset. The first constraint implies that all asset weights should sum to one. k is the required return on the portfolio, so, the second constraint implies that the weighted sum of the returns of each constituent in the portfolio is the required rate of return. In the mean-variance model, expected return and variance are exogenous to the model. This implies that, for example, the variance incorporates other sources of agricultural risk such as yield and production risk. I also focus on risk-based portfolio selection, which minimizes risk without restricting the expected return. In this chapter, I focus on three portfolio selection strategies, the naïve equal-weight portfolio, the minimum variance portfolio, and the maximum reward-to-risk portfolio. In an equal-weight portfolio, each constituent has the same weight in the portfolio. The minimum-variance portfolio is the mean-variance portfolio selection model but without the required return constraint. In other words, it minimizes the portfolio risk disregarding any required rate of return. The maximum reward-to-risk portfolio has the following model:

$$\max_{X} \frac{\boldsymbol{X}`\mathrm{C}}{(\boldsymbol{X}`\,\Omega\,\boldsymbol{X})^{1/2}} \tag{4}$$

$$S.T\ \ \boldsymbol{X}`\boldsymbol{1} = 1. \tag{5}$$

The numerator of the objective function is the portfolio return while the denominator is the standard deviation (volatility) of the portfolio return.

In addition, I estimate the beta of each farmland location/quality. I use the Capital Asset Pricing Model (CAPM) of Sharpe and Lintner to estimate the systematic risk for each farmland location/quality. According to the CAPM model:

$$E\left(R_{ij}\right) = R_f + \beta_{ij}\left[\left(E(R_m) - R_f\right)\right] \tag{6}$$

where $E\left(R_{ij}\right)$ is the expected return of farmland quality i in location *j*. R_f is the rate of return on the risk-free asset, β_{ij} is the systematic risk associated with farmland quality i in location *j* and $E(R_m)$ is the expected market return. Based on this CAPM formula, the only risk that affects asset price is market risk. Previous literature provides several extensions of the CAPM by including other risk factors. With respect to the farmland market, Irwin *et al*. (1988) added uncertain inflation and Bjornson (1994) added changes in expected inflation, bond yield curve, and term structure of interest rates. The beta (β_{ij}) is estimated by regression asset's excess return on market excess return where the slope of the regression corresponds to the beta of the asset (i.e. farmland location/quality).

2.4 Data

Data for farmland values and cash rents of different farmland location/quality is obtained for two corn-belt states, namely Indiana and Iowa. In Indiana, I rely on the Purdue Agricultural Economics Report (PAER) published by Purdue University. PAER has been published on annual basis since 1974, and involves data about land values and cash rents in the state of Indiana. These data are typically survey data where the respondents to the survey are appraisers, commercial banks, loans officers, FSA personnel, farmers, and farm managers. PAER shows the average estimated Indiana farmland value and the annual percentage change by location and land quality. Data covers six Indiana regions (North, Northeast, West Central, Central, Southwest, and Southeast) and three land qualities (Top, Average, and Poor).

For Iowa farmland values and cash rents, I relied on the Farmland Value Survey sponsored by Iowa State University. The Iowa Farmland Value Survey is sent to farm managers, licensed real estate brokers, appraisers, agricultural lenders, county assessors, and other individuals who are familiar with farmland markets. It has been published each year since 1941. Like PAER, the Iowa Farmland Value Survey provides information about the average farmland value for three land classes (Top, Average, and Poor) and for nine Iowa regions. The period of the study is 1974 - 2018. This is the period that we have data for both Indiana and Iowa. In addition to farmland data, I obtained data for the S&P 500 and 3-month T-bills as a risk-free rate. Farmland is a long-lived asset. That is why some studies used long-run government loan rates as a proxy for risk-free rate. This is useful to account for reinvestment risk. This choice, however, ignores inflation risk. Choosing short-term interest rate accounts for this inflation risk. In addition, demand for farmland is heavily dependent on access to credit which is strongly related to short-term interest rate. This is the main motivation for us to rely on three-month T-bills rate as proxy for the risk-free rate. Return data on S&P 500 is obtained from the Center for Research in Security Prices (CRSP).

2.5 Empirical Results

2.5.1 Descriptive statistics

In this section, I begin by showing descriptive statistics and correlations results for Indiana and Iowa. Farmland data are decomposed by location and quality. Tables 2.1 and 2.2 illustrate the descriptive statistics for the annual returns on farmland locations/qualities of Indiana and Iowa, respectively. As can be seen from table 2.1, the average returns for Indiana farmland ranged from 10% to 12%. The standard deviation ranged from 9% to 15%. This indicates that the dispersion of risk (9% - 15%) is larger than the dispersion of mean return (10% - 12%). This implies larger room for risk minimization than for return maximization when forming portfolios. The reward-to-risk ratio, as a measure of reward per unit of risk, ranged from 0.75 for the top farmland quality in the central region (C.top) of Indiana to 1.18 for average farmland quality in the southeast region (SE. AVG) of Indiana. The difference between the lowest and highest reward-to-risk ratio (0.435) suggests that return and risk vary across regions in Indiana. It is worth noting that Indiana southeast region has the greatest reward-to-risk ratio across all the Indiana six regions and that the average quality farmland in southeast Indiana has the highest reward-to-risk ratio.

Table 2.1: Descriptive Statistics of Annual Returns for Indiana 1975 – 2018

	Mean	St.Deviation	Variance	Min	Max	Reward-to-risk Ratio
NE.TOP	0.107	0.123	0.015	0.203	0.415	0.864
NE.AVG	0.110	0.119	0.014	0.174	0.381	0.924
NE.POOR	0.116	0.129	0.017	0.154	0.437	0.903
WC.TOP	0.111	0.134	0.018	0.140	0.550	0.830
WC.AVG	0.113	0.128	0.016	0.150	0.497	0.887
WC.POOR	0.117	0.130	0.017	0.213	0.437	0.902
C.Top	0.099	0.132	0.017	0.138	0.540	0.745
C.AVG	0.112	0.126	0.016	0.146	0.601	0.891
C.POOR	0.111	0.132	0.018	0.179	0.618	0.839
SE.TOP	0.108	0.099	0.010	0.108	0.383	1.096
SE.AVG	0.108	0.092	0.008	0.092	0.352	1.181
SE.POOR	0.108	0.106	0.011	0.092	0.389	1.019
SW.TOP	0.114	0.147	0.022	0.209	0.491	0.778
SW.AVG	0.111	0.134	0.018	0.198	0.437	0.830
SW.POOR	0.116	0.143	0.020	0.209	0.575	0.810
N.TOP	0.111	0.133	0.018	0.138	0.581	0.833
N.AVG	0.115	0.131	0.017	0.140	0.530	0.878
N.POOR	0.115	0.138	0.019	0.169	0.487	0.835

This table presents the descriptive statistics for the three levels of farmland quality (Top, Average, Poor) for the six Indiana regions (northeast NE, north N, central C, west central WC, southwest SW, and southeast SE). Reward to risk ratio is obtained by dividing farmland return by standard deviation of that return. These estimates are based on land values and cash rent data published by Purdue Agricultural Economics Report (PAER).

Table 2.2: Descriptive Statistics of Annual Returns for Iowa 1975 -2018

	Mean	St. Deviation	Variance	Min	Max	Reward-to-Risk Ratio
Top.NW	0.062	0.143	0.020	0.293	0.336	0.435
Avg.NW	0.064	0.147	0.022	0.297	0.429	0.434
Poor.NW	0.064	0.145	0.021	0.332	0.378	0.444
Top.NC	0.054	0.142	0.020	0.329	0.378	0.385
Avg.NC	0.058	0.139	0.019	0.354	0.387	0.413
Poor.NC	0.060	0.141	0.020	0.338	0.309	0.423
Top.NE	0.062	0.139	0.019	0.297	0.372	0.449
Avg.NE	0.065	0.137	0.019	0.315	0.349	0.475
Poor.NE	0.067	0.132	0.017	0.328	0.310	0.509
Top.WC	0.060	0.137	0.019	0.282	0.350	0.442
Avg.WC	0.063	0.138	0.019	0.289	0.366	0.458
Poor.WC	0.065	0.142	0.020	0.299	0.346	0.457
Top.C	0.054	0.133	0.018	0.324	0.328	0.407
Avg.C	0.058	0.135	0.018	0.336	0.340	0.427
Poor.C	0.057	0.130	0.017	0.286	0.302	0.441
Top.EC	0.057	0.123	0.015	0.281	0.410	0.462
Avg.EC	0.059	0.118	0.014	0.309	0.307	0.501
Poor.EC	0.061	0.120	0.014	0.326	0.274	0.506
Top.SW	0.061	0.125	0.016	0.288	0.390	0.487
Avg.SW	0.062	0.127	0.016	0.264	0.341	0.488
Poor.SW	0.063	0.137	0.019	0.279	0.333	0.462
Top.SC	0.058	0.124	0.015	0.245	0.313	0.468
Avg.SC	0.060	0.125	0.016	0.248	0.292	0.478
Poor.SC	0.065	0.132	0.018	0.311	0.291	0.488
Top.SE	0.053	0.114	0.013	0.277	0.341	0.462
Avg.SE	0.057	0.117	0.014	0.275	0.349	0.487

This table presents the descriptive statistics for the three levels of farmland quality (Top, Average, Poor) for the nine Iowa regions (north east NE, north west NW, north central NC, central C, west central WC, east central EC, southwest SW, south central, and southeast SE). Reward to risk ratio is obtained by dividing farmland return by standard deviation of that return These estimates are based on land values and cash rent data published by Iowa Farmland Value Survey.

As evident in table 2.2, for Iowa, the mean returns for different farmland locations/qualities ranged from 5% to 6%. The standard deviation ranges from 11% to 15%. At first glance, it appears that Indiana farmland has, on average, a better risk-return relationship than Iowa farmland. This is obvious when we compare the ranges of reward-to-risk ratio (0.4 to 0.5) for Iowa and Indiana farmland for which the reward-to-risk ratios ranges from 0.75 to 1.18. The highest reward-to-risk ratio for Iowa farmland is 0.509 for the poor-quality farmland in Northeastern Iowa. The lowest reward-to-risk ratio in Iowa farmland is 0.385 for the top-quality farmland in North Central Iowa.

2.5.2 Correlation Results

Table 2.3 reports the correlation coefficients for Indiana farmland. Although the correlation among qualities within districts are strongly positive, it is noticeable that the lowest correlation is between the top and poor qualities. The average correlation between top and poor qualities are 0.86 compared to the correlation coefficients of 0.94 and 0.92 between the top and average qualities, and the average and poor qualities respectively. The high correlation values suggest that the potential for diversifying across quality alone is low. For instance, figure 2.1 shows the time series of farmland value per acre in Indiana for each farmland quality (top, average, and poor). The time series are nearly parallel indicating that all the values of farmland qualities move up and down together. In other words, there is little diversification benefit within the space of farmland qualities alone. That is why my focus in this chapter is on the two dimensions of farmland quality and location.

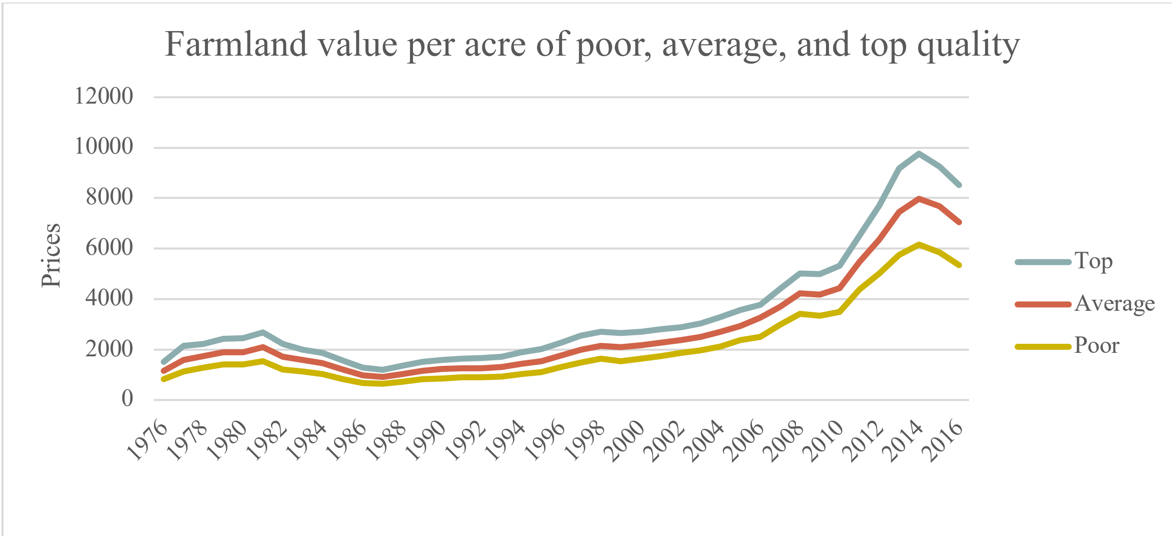

Figure 2.1: Indiana Farmland Value per Acre of Poor, Average, and Top Quality

This figure shows the average value per acre of the three farmland qualities (poor, average, top) in Indiana over the period 1976-2016. These land values are obtained from Purdue Agricultural Economics Report (PAER).

Table 2.3: Correlation between Farmland Qualities in each of the Six Regions in Indiana

	North				*Northeast*		
	TOP	*AVG*	*POOR*		*TOP*	*AVG*	*POOR*
TOP	1			TOP	1		
AVG	0.985	1		AVG	0.974	1	
POOR	0.933	0.964	1	POOR	0.880	0.925	1
	West Central				*Central*		
	TOP	*AVG*	*POOR*		*Top*	*AVG*	*POOR*
TOP	1			Top	1		
AVG	0.982	1		AVG	0.935	1	
POOR	0.938	0.970	1	POOR	0.918	0.964	1
	Southeast				*Southwest*		
	TOP	*AVG*	*POOR*		*TOP*	*AVG*	*POOR*
TOP	1			TOP	1		
AVG	0.917	1		AVG	0.854	1	
POOR	0.706	0.825	1	POOR	0.770	0.859	1

This table presents the correlation between the three farmland qualities (top, average, poor) in each of the six regions in Indiana (Northeast, North, Central, West Central, South West, and Southeast). These correlations are based on land values and cash rent data published by Purdue Agricultural Economics Report (PAER).

I also examined the correlation between locations and qualities within Indiana. The table is not included in the chapter to save space and is available upon request. Correlation coefficients between different locations/qualities within Indiana are all positive yet widely dispersed with an average correlation of 0.78. The lowest correlation coefficients are also between the top- and poor-quality farmland. The minimum correlation (i.e., 0.39) is between the top southeast top-quality farmland and the northeast poor-quality farmland. Looking at these results and table 2.3, it appears that there is potential for diversifying across locations and qualities in Indiana.

Correlation coefficients between farmland qualities in Iowa are presented in table 2.4. The correlation coefficients between Iowa farmland qualities are quite a bit higher than those in Indiana.

The average correlation between Iowa top and average quality is 0.97. Correlation between Iowa average and poor farmland qualities is 0.94, while the lowest average correlation is between the top and poor farmland qualities (0.91). Like Indiana, the correlation between the top and poor qualities is the lowest. I did the correlation analysis for each location/quality in Iowa. However, to save space, I have not included a table containing these results. The table is available upon request. The minimum correlation is 0.68, which was between poor quality, southeast Iowa farmland and average quality, northwest Iowa farmland. This also indicates the possibility for diversification benefits in Iowa across location/qualities.

Table 2.4: Correlation between Farmland Qualities in each of the Nine Regions in Iowa

Northwest				*North Central*			
	Top	*Avg*	*Poor*		*Top*	*Avg*	*Poor*
Top	1			Top	1		
Avg	0.984	1		Avg	0.987	1	
Poor	0.960	0.974	1	Poor	0.962	0.981	1
Northeast				*West Central*			
	Top	*Avg*	*Poor*		*Top*	*Avg*	*Poor*
Top	1			Top	1		
Avg	0.980	1		Avg	0.992	1	
Poor	0.941	0.962	1	Poor	0.951	0.965	1
Central				*East Central*			
	Top	*Avg*	*Poor*		*Top*	*Avg*	*Poor*
Top	1			Top	1		
Avg	0.992	1		Avg	0.924	1	
Poor	0.953	0.968	1	Poor	0.890	0.940204	1
Southwest				*South Central*			
	Top	*Avg*	*Poor*		*Top*	*Avg*	*Poor*
Top	1			Top	1		
Avg	0.979	1		Avg	0.970	1	
Poor	0.929	0.964	1	Poor	0.857	0.892	1

Southeast			
	Top	*Avg*	*Poor*
Top	1		
Avg	0.959	1	
Poor	0.846	0.903	1

This table presents the correlation between the three farmland qualities (top, average, poor) in each of the nine regions in Iowa (North East, North West, North Central, Central, West Central, East Central, South West, South Central, and South East). These correlations are based on land values and cash rent data published by Iowa Farmland Value Survey

2.5.3 CAPM Results

In this subsection, I estimate α and systematic risks β for location/qualities in Indiana and Iowa. Table 2.5 shows these estimates for Indiana by location and quality. Generally speaking, the CAPM results in table 2.5 are consistent with prior literature. The estimate of excess farmland returns (α_s) range from 0.06 to 0.08, and are economically and statistically significant. Nonzero alphas for farmland locations/qualities in Indiana indicate that incorporating Indiana farmland locations/qualities into a well-diversified benchmark portfolio improve the Sharpe ratio and/or reward-to-risk ratio of the new portfolio. β estimates are statistically indistinguishable from zero indicating that farmland has weak correlation (or covariance) with the overall market index. This weak correlation with the S&P 500 makes farmland a good diversifier of risk and suggest the inclusion of it in mixed asset portfolios. The low beta of farmland is consistent with previous studies such as Baker *et al*. (2014).

Table 2.5: CAPM Results for Indiana

Farmland Location and Quality	**α**	**p-value**	**β**	**p-value**
NE top	0.059	0.007	0.066	0.607
NE average	0.062	0.004	0.087	0.491
NE Poor	0.068	0.000	0.093	0.496
WC top	0.066	0.007	0.027	0.850
WC average	0.069	0.003	0.015	0.912
WC Poor	0.070	0.003	0.054	0.695
C top	0.055	0.017	-0.011	0.937
C average	0.064	0.000	-0.051	0.609
C Poor	0.064	0.007	0.063	0.651
SE top	0.064	0.001	-0.056	0.598
SE average	0.064	0.000	-0.051	0.421
SE poor	0.057	0.002	0.088	0.420
SW Top	0.075	0.004	-0.103	0.504
SW Avg	0.070	0.003	-0.073	0.598
SW poor	0.072	0.005	0.001	0.996
N Top	0.068	0.005	-0.028	0.839
N average	0.072	0.003	-0.020	0.886
N poor	0.070	0.004	0.021	0.882

This table presents the αs and βs of each farmland quality at each region in Indiana. Results are based on annual data from Purdue Agricultural Economics Report (PAER) for 1974 –2018. αs and βs are estimated by regressing the excess return of different farmland qualities/locations on the excess market return which is proxied by the difference between the return on S&P 500 and the 3-month treasury bills.

In table 2.6, I show the α and β of different farmland location/qualities in Iowa. Unlike the results for Indiana, excess return for Iowa locations/qualities are not significant either economically or statistically. The β estimates were also insignificant.

Table 2.6: CAPM Results for Iowa

Farmland Location and Quality	α	p-Value	β	p-Value
Top.NW	0.015	0.556	0.046	0.766
Avg.NW	0.018	0.482	0.035	0.823
Poor.NW	0.018	0.483	0.048	0.756
Top.NC	0.010	0.699	0.014	0.924
Avg.NC	0.013	0.592	0.008	0.960
Poor.NC	0.014	0.564	0.026	0.865
Top.NE	0.018	0.465	0.007	0.961
Avg.NE	0.019	0.416	0.028	0.847
Poor.NE	0.021	0.376	0.052	0.716
Top.WC	0.015	0.546	0.035	0.813
Avg.WC	0.017	0.496	0.054	0.720
Poor.WC	0.020	0.421	0.012	0.938
Top.C	0.008	0.730	0.037	0.799
Avg.C	0.011	0.635	0.046	0.750
Poor.C	0.011	0.620	0.039	0.785
Top.EC	0.012	0.582	0.014	0.918
Avg.EC	0.017	0.419	-0.038	0.770
Poor.EC	0.019	0.366	-0.053	0.683
Top.SW	0.015	0.494	0.032	0.813
Avg.SW	0.016	0.468	0.030	0.829
Poor.SW	0.017	0.475	0.035	0.813
Top.SC	0.017	0.437	-0.068	0.617
Avg.SC	0.016	0.460	-0.020	0.880
Poor.SC	0.024	0.301	-0.081	0.574
Top.SE	0.007	0.746	0.040	0.757
Avg.SE	0.008	0.716	0.109	0.400
Poor.SE	0.011	0.618	0.062	0.634

This table presents the αs and βs of each farmland quality at each region in Indiana. Results are based on annual data from Iowa Farmland Value Survey for 1974 –2018. α and β are estimated by regressing the excess return of different farmland qualities/locations on the excess market return which is proxied by the difference between the return on S&P 500 and the 3-month treasury bills

2.5.4 Portfolio Analysis

In this section, I perform a portfolio analysis of Indiana and Iowa farmland location/qualities. Diversification benefits are apparent when we compare the reward-to-risk ratios in table 2.1 to the reward-to-risk ratios of three portfolio selection rules (equal weight, minimum variance, and maximum reward-to-risk ratio portfolios). As shown in table 2.7, the reward-to-risk ratio of minimum variance and maximum reward-to-risk ratio portfolios are greater than the reward-to-risk ratio of individual location/quality farmland in the state of Indiana. It is also evident that the farmland that has the highest reward-to-risk ratio (SE.Avg which has reward-to-risk ratio of 1.18 from table 1) has the dominant weight in minimum variance and maximum reward-to-risk ratio portfolios. The portfolio weight of SE.Avg farmland in the minimum variance and maximum reward-to-risk ratio portfolios are 71% and 67%, respectively. This indicates that, from a portfolio perspective, the average quality farmland in Indiana is more attractive relative to top- and poor-quality farmland. Table A-II in the appendix shows the alpha α and Beta β of the minimum-variance and maximum reward-to-risk ratio portfolios of Indiana farmland.

It is also interesting to note that the relatively low correlation between the southeast and northeast Indiana farmland is reflected in the portfolio weights in the minimum variance portfolio and maximum reward-to-risk ratio portfolio. As evident in table 2.7, most of the portfolio weights in the aforementioned portfolios are concentrated in these two regions.

Table 2.7: Portfolio Analysis of Indiana Farmland

	Equal Wt	Min Var	Max Reward-to-Risk Ratio
NE.TOP	5.56%	11.98%	0.00%
NE.AVG	5.56%	0.00%	24.08%
NE.POOR	5.56%	11.67%	4.54%
WC.TOP	5.56%	0.00%	0.00%
WC.AVG	5.56%	0.00%	0.00%
WC.POOR	5.56%	0.00%	0.00%
C.Top	5.56%	0.00%	0.00%
C.AVG	5.56%	0.00%	0.00%
C.POOR	5.56%	0.00%	0.00%
SE.TOP	5.56%	1.97%	0.00%
SE.AVG	5.56%	70.90%	66.74%
SE.POOR	5.56%	0.00%	0.00%
SW.TOP	5.56%	3.48%	4.64%
SW.AVG	5.56%	0.00%	0.00%
SW.POOR	5.56%	0.00%	0.00%
N.TOP	5.56%	0.00%	0.00%
N.AVG	5.56%	0.00%	0.00%
N.POOR	5.56%	0.00%	0.00%
sum	100%	100 %	100 %
μ	0.112	0.110	0.111
σ	0.110	0.085	0.086
μ/σ	1.018	1.292	1.299

In this table, I apply three portfolio strategies (equal weight, minimum-variance, and maximum reward-to-risk ratio portfolios) on different farmland location/qualities in Indiana. Equal Wt portfolio strategy is the portfolio formed by giving equal weight to each farmland location/quality. Min Var portfolio is this portfolio formed my minimizing the portfolio risk without constraining the return level. Max Reward-to-Risk ratio portfolio is the portfolio that maximize the ratio of portfolio return to its standard deviation. Data is obtained from Purdue Agricultural Economics Report (PAER). μ and σ are the portfolio return and standard deviation, respectively.

Table 2.8 shows the portfolio performance for location/qualities of Iowa farmland. Unlike Indiana location/qualities, Iowa farmland shows very little (or even negligible) improvement in diversification benefits. The difference between the highest reward-to-risk ratio of individual location/quality Iowa farmland (0.508) and the maximum reward-to-risk ratio of Iowa farmland (0.540) is only 0.032, a negligible difference.

Table 2.8: Portfolio Analysis of Iowa Farmland

	Equal Wt	**Min Var**	**Max Reward-to-Risk Ratio**
Top.NW	0.037	0.000	0.000
Avg.NW	0.037	0.000	0.000
Poor.NW	0.037	0.000	0.000
Top.NC	0.037	0.000	0.000
Avg.NC	0.037	0.000	0.000
Poor.NC	0.037	0.000	0.000
Top.NE	0.037	0.000	0.000
Avg.NE	0.037	0.000	0.000
Poor.NE	0.037	0.000	0.136
Top.WC	0.037	0.000	0.000
Avg.WC	0.037	0.000	0.000
Poor.WC	0.037	0.000	0.000
Top.C	0.037	0.000	0.000
Avg.C	0.037	0.000	0.000
Poor.C	0.037	0.000	0.000
Top.EC	0.037	0.000	0.000
Avg.EC	0.037	0.221	0.027
Poor.EC	0.037	0.000	0.242
Top.SW	0.037	0.000	0.000
Avg.SW	0.037	0.000	0.042
Poor.SW	0.037	0.000	0.000
Top.SC	0.037	0.059	0.000
Avg.SC	0.037	0.000	0.000
Poor.SC	0.037	0.033	0.304
Top.SE	0.037	0.408	0.000
Avg.SE	0.037	0.000	0.170
Poor.SE	0.037	0.280	0.079
sum	1.000	1.000	1.000
μ	0.060	0.056	0.062
σ	0.124	0.109	0.115
μ/σ	0.488	0.515	0.540

In this table, I apply three portfolio strategies (equal weight, minimum-variance, and maximum reward-to-risk ratio portfolios) on different farmland location/qualities in Iowa. Equal Wt portfolio strategy is the portfolio formed by giving equal weight to each farmland location/quality. Min Var portfolio is this portfolio formed my minimizing the portfolio risk without constraining the return level. Max Reward-to-Risk ratio portfolio is the portfolio that maximize the ratio of portfolio return to its standard deviation. Data is obtained from Iowa Farmland Value Survey. μ and σ are the portfolio return and standard deviation, respectively.

2.5.5 Robustness Check

In this sub-section, I conduct a robustness check for the diversification potential of locations/qualities of Indiana farmland. In the previous section, we observed that farmland in southeast Indiana has a dominant weight in the minimum variance and maximum reward-to-risk ratio portfolios. As a robustness check, I omit southeast Indiana from the assets considered in the portfolio. My aim is to see whether there is a significant improvement of the reward-to-risk ratio. As shown in table A1 in the appendix, there is a significant improvement in reward-to-risk ratio of the portfolios even without including farmland in the southeast region. The reward-to-risk ratios of the minimum variance and maximum reward-to-risk ratios portfolios are significantly greater than the reward-to-risk ratios of individual location/quality in Indiana.

2.5.6 Diversifying across Quality

In this section, I examine whether geographic diversification benefits are enhanced by adding a second diversification dimension, farmland quality. In order to investigate this, we need to compare the reward-to-risk ratios of different portfolio selection strategies before and after introducing the quality dimension to the geographic dimension of portfolio analysis. In doing so, I formulated portfolios with the same quality in different geographic regions in Indiana. There is no need to perform the same analysis for Iowa because, as shown in the previous section, there is no significant diversification benefits for diversifying across location/quality in Iowa.

Table 2.9 shows the performance of portfolios based solely on geographic diversification holding farmland quality constant. The reward-to-risk ratios of the three portfolio allocation strategies are less than the reward-to-risk ratios when quality is added to the geographic allocation (shown in table 2.7). In addition, what is evident in table 2.9 is the relative attractiveness of southeast farmland with its three farmland qualities in terms of risk and return compared to other regions in Indiana. Other than the equal weighted portfolio, Indiana southeast farmland has the dominant weight regardless of the farmland quality. For example, as shown in table 2.9, top-quality southeast Indiana farmland had a weight of the of 0.68 in the minimum variance portfolio and 0.65 of maximum reward-to-risk ratio portfolio. Average and poor southeast Indiana farmland also had the dominant weight in the minimum variance and maximum reward-to-risk ratio portfolio.

Table 2.9: Geographic Diversification for Indiana Holding Quality Constant

		Panel A: Top Farmland	
	Equal Wt	***Min Var***	***Max Reward-to-Risk Ratio***
NE.TOP	0.167	0.202	0.154
WC.TOP	0.167	0	0.028
C.Top	0.167	0	0
SE.TOP	0.167	0.675	0.652
SW.TOP	0.167	0.079	0.152
N.TOP	0.167	0.0433	0.015
sum	1	1	1
μ	0.110	0.109	0.110
σ	0.109	0.090	0.091
μ/σ	1.002	1.209	1.214

Table 2.9 continued

	Panel B: Average Farmland		
	Equal Wt	***Min Var***	***Max Reward-to-Risk Ratio***
NE.AVG	0.167	0.223	0.256
WC.AVG	0.167	0	0
C.AVG	0.167	0	0
SE.AVG	0.167	0.777	0.745
SW.AVG	0.167	0	0
N.AVG	0.167	0	0
sum	1	1	1
μ	0.112	0.110	0.110
σ	0.109	0.087	0.087
μ/σ	1.030	1.266	1.267

	Panel C: Poor Farmland		
	Equal Wt	***Min Var***	***Max Reward-to-Risk Ratio***
NE.POOR	0.167	0.339	0.353
WC.POOR	0.167	0	0
C.POOR	0.167	0	0
SE.POOR	0.167	0.661	0.647
SW.POOR	0.167	0	0
N.POOR	0.167	0	0
sum	1	1	1
μ	0.113	0.112	0.112
σ	0.116	0.100	0.100
μ/σ	0.977	1.118	1.118

This table shows the return, standard deviation, and reward-to-risk ratios of three portfolio strategies (equal weight, minimum variance, and maximum reward-to-risk ratios) holding the quality level unchanged. Panel A represents analysis for top-quality farmland in Indiana. Panels B and C represent analysis for average and low-quality Indiana farmland. Equal Wt portfolio strategy is the portfolio formed by giving equal weight to each farmland location/quality. Min Var portfolio is this portfolio formed my minimizing the portfolio risk without constraining the return level. Max Reward-to-Risk ratio portfolio is the portfolio that maximize the ratio of portfolio return to its standard deviationThese estimates are based on farmland values and cash rent data from Purdue Agricultural Economics Report (PAER).

2.5.7 Portfolios of farmlands in Indiana and Iowa

In this section, I look at the potential of geographic diversification of Indiana and Iowa farmland. Results are not in favor of Iowa farmland. This is also indicated by the correlation between farmland returns in Indiana and Iowa. For example, the minimum correlation for the location/quality combination in Indiana is 0.39, while the minimum correlation in Iowa is 0.68. When I merge Indiana and Iowa into one correlation matrix, this location/quality matrix has a dimension of 45 x 45, I found that the minimum correlation is still 0.39 which is between the southeast top-quality farmland and the northeast poor-quality farmland in Indiana. This indicates that there are very little diversification benefits for combining Indiana and Iowa farmland into a single portfolio.

In addition, tables 2.1 and 2.2 show a big difference between reward-to-risk ratios in Indiana and Iowa. The average reward-to-risk ratio in Indiana is 0.90 while it is 0.46 in Iowa. This explains why the maximum reward-to-risk ratio portfolio illustrated in table 2.10 has zero weights for Iowa locations/qualities combinations. In other words, the maximum reward-to-risk ratio portfolio is the same as a portfolio without adding Iowa farmland to the asset space. The minimum variance portfolio, however, does include average quality farmland in southeast Iowa. It is important to note the large improvement in the reward-to-risk ratio moving from the equal weight portfolio strategy to the minimum variance and maximum reward-to-risk ratio portfolios. The equal-weight portfolio is clearly not optimal.

Table 2.10: Portfolio Analysis of Indiana Farmland

	Equal Wt.	Min Var	Max Reward-to-Risk Ratio
	-		
	-	0.146 (NE. Top.IN)	0.240 (NE.Avg.IN)
	-	0.006 (NE. Poor.IN)	0.048 (NE. Poor. IN)
	-	0.665 (SE.Avg.IN)	0.668 (SE.Avg. IN)
	-	0.010 (SW.Poor.IN)	0.044 (SW. Top. IN)
	-	0.172 (Avg.Se. IO)	-
sum	1.000	1.000	1.000
μ	0.081	0.100	0.111
σ	0.112	0.084	0.086
μ/σ	0.723	1.192	1.299

In this table, I apply three portfolio strategies (equal weight, minimum-variance, and maximum reward-to-risk ratio portfolios) to different farmland location/qualities in Indiana (IN) and Iowa (IO). Equal Wt portfolio strategy is the portfolio formed by giving equal weight to each farmland location/quality. Min Var portfolio is this portfolio formed my minimizing the portfolio risk without constraining the return level. Max Reward-to-Risk ratio portfolio is the portfolio that maximize the ratio of portfolio return to its standard deviation. Indiana data is obtained from Purdue Agricultural Economics Report (PAER) While Iowa data are obtained from Iowa Farmland Value Survey. μ and σ are the portfolio return and standard deviation respectively.

Previous discussion contributes to the fact that, even though they are both Corn Belt states, there are major differences in farmland investments in Indiana and Iowa. Over the period covered in this analysis, the average price of farmland was higher in Indiana than in Iowa. Figure 2.2 shows the difference between the average price of medium quality farmland in Indiana and the average price of medium quality farmland in Iowa. In almost 90% of the years, prices in Indiana were higher than prices in Iowa.

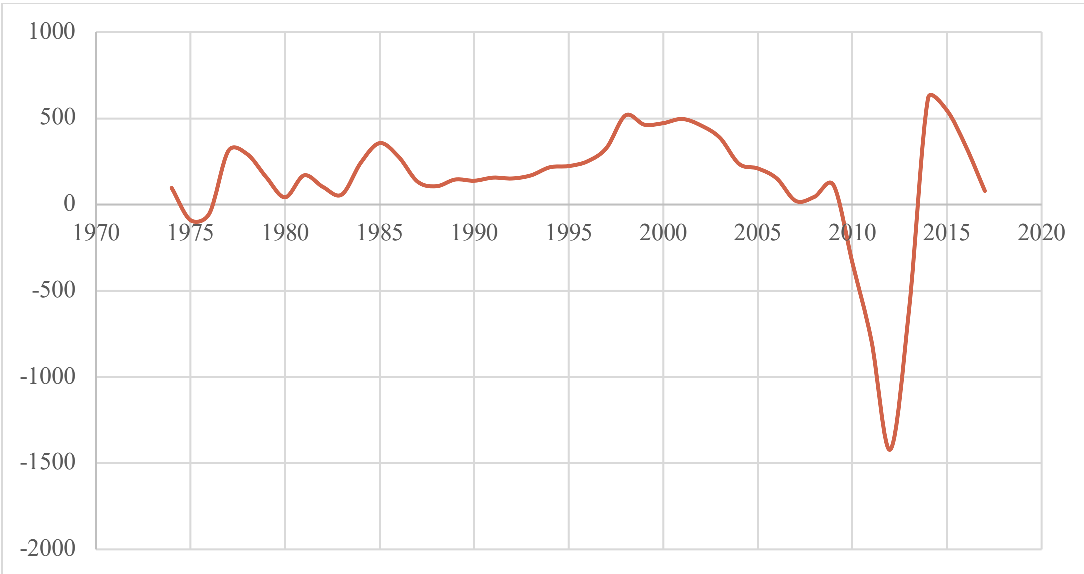

Figure 2.2: Price Difference of Indiana and Iowa Medium Quality Farmland
Indiana – Iowa

This figure reports the difference between price of Indiana medium quality farmland and Iowa medium quality farmland (Indiana Price – Iowa Price) over the period 1976 – 2016. Indiana data is obtained from Purdue Agricultural Economics Report (PAER) While Iowa data are obtained from Iowa Farmland Value Survey.

In the same vein, Langemeier *et al*. (2016) examined the trends in farmland values and cash rents in the states on Indiana, Illinois, and Iowa. They compared the Price/rent ratios of farmland in the three states for the period 1973 to 2015. In almost all of this period, the Price/rent ratio was higher in Indiana than in Iowa.

2.6 Conclusions

This chapter examines the investment performance of different farmland qualities for different geographic regions in Indiana and Iowa. Essentially, this chapter discusses the risk and return of different farmland location/qualities in these two states. Indiana and Iowa were chosen for two reasons. First, farmland value and cash rent data were available for each farmland quality and each geographic region in these two states. Second, both states are corn belt states. Thus, similar crops are produced in these two states.

My findings confirm the role of farmland highlighted in prior literature as an attractive asset class relative to other capital assets. Farmland still outperforms other capital assets in terms of risk and return. I went a step further by considering the heterogeneity of farmland. Even though there are different farmland soil qualities, their systematic risks are not systematically different from each other. The betas of different farmland qualities for different regions in Indiana and Iowa are all around zero. Excess returns range 0.06 to 0.08 in Indiana but they are not statistically different from zero in Iowa.

The average correlation between farmland qualities in each region in Indiana and Iowa are 0.78 and 0.90, respectively, indicating that there are more diversification benefits in Indiana farmland. The portfolio analysis also underscored the attractiveness of southeast Indiana farmland relative to other farmland in Indiana. Its relative portfolio weight in the minimum variance and the maximum reward-to-risk ratio portfolio significantly dominated farmland in other regions.

My analysis of whether quality diversification improve the performance of geographically diversified portfolio reveals mixed results. I approached this goal by holding the quality level constant and diversifying geographically and then I compared the reward-to-risk ratio of the geographically diversified portfolio to the location/quality portfolio. I found that the reward-to-risk ratio of the latter portfolio is larger than that of the former one. Adding a quality dimension to the geographic dimension provided significant improvement in the reward-to-risk ratio in Indiana farmland, but not for Iowa. In addition, in contrast to the excess returns for Iowa farmland, the excess returns for Indiana farmland were significantly different from zero.

This study paves the path for considering diversification across quality. The mixed results in my study may motivates future researchers to dig deeper into examining the risk and return of farmland quality either using similar datasets or looking at transaction data on farmland sales.

Based on data on farmland in Indiana and Iowa, the quality dimension alone does not have as large of diversification benefits as combining both the quality and location dimensions.

2.7 References

Baker, T.G., Boehlje, M.D., and Langemeier, M.R. (2014). Farmland: is it currently priced as an attractive investment? *American Journal of Agricultural Economics*, 96(5), 1321-1333

Barry, P.J. (1980). Capital asset pricing and farm real estate. *American Journal of Agricultural Economics*, 62(3), 549-553.

Bjornson, B., and Innes, R. (1992). Another look at returns to agricultural and nonagricultural assets. *American Journal of Agricultural Economics*, 74(1), 109-119.

Bjornson, B. (1994). Asset pricing theory and the predictable variation in agricultural asset returns. *American Journal of Agricultural Economics*, 76(3), 454-464.

Burns, C., Key, N., Tulman, S., Borchers, A., and Weber, J. (2018). Farmland Values, Land Ownership, and Returns to Farmland, 2000-2016 (No. 1477-2018-5469).

Ervin, E.D., and J.W. Mill. 1985. "Agricultural Land Markets and Soil Erosion: Policy Relevance and Conceptual Issues." *American Journal of Agricultural Economics*, 67 (5): 938-56.

Gardner, K., and Barrows, R. (1985). "The impact of soil conservation investments on land prices." *American Journal of Agricultural Economics,* 67, 943–947

Hardin, W.G., and Cheng, P. (2002). Farmland investment under conditions of certainty and uncertainty. *The Journal of Real Estate Finance and Economics*, 25(1), 81-98.

Irwin, S.H., Forster, D.L., and Sherrick, B.J. (1988). Returns to farm real estate revisited. *American Journal of Agricultural Economics*, 70(3), 580-587.

Kuethe, T. H., Walsh, N., & Ifft, J. (2013). Farmland versus Alternative Investments Before and After the 2008 Financial Crisis. *Journal of the ASFMRA*, 76(1), 120–131.

Langemeier, M., Baker, T., and Boehlje, M. (2016), Trends in Land Prices, Cash Rents, and Price to Rent Ratios, for Iowa, Illinois, and Indiana. *Center for Commercial Agriculture*.

Lins, D.A., Sherrick, B.J., and Venigalla, A. (1992). Institutional portfolios: diversification through farmland investment. *Real Estate Economics*, 20(4), 549-571.

Ma, S., and Swinton, S.M. (2012). Hedonic valuation of farmland using sale prices versus appraised values. *Land Economics*, 88(1), 1-15.

Miranowski, J.A., and Hammes, B.D. (1984). Implicit prices of soil characteristics for farmland in Iowa. *American journal of agricultural economics*, 66(5), 745-749.

Nickerson C, Morehart M, Kuethe T, Beckman J, Ifft J & Williams R (2012) Trends in U.S. Farmland Values and Ownership. EIB-92. U.S. Dept. of Agriculture, Econ. Res. Serv.

Palmquist, R.B., and Danielson, L.E. (1989). A hedonic study of the effects of erosion control and drainage on farmland values. *American journal of agricultural economics*, 71(1), 55-62.

Sklenicka, P., Molnarova, K., Pixova, K.C., and Salek, M.E. (2013). Factors affecting farmland prices in the Czech Republic. *Land Use Policy*, 30(1), 130-136.

2.8 Appendix

Table A-I
Portfolio Analysis of Indiana Farmland Without Southeast Region

	Equal Wt	Min Var	Max Reward-to-Risk Ratio
NE.TOP	6.67%	0.00%	0.00%
NE.AVG	6.67%	59.54%	79.47%
NE.POOR	6.67%	0.00%	0.00%
WC.TOP	6.67%	0.00%	0.00%
WC.AVG	6.67%	0.00%	0.00%
WC.POOR	6.67%	0.00%	0.00%
C.Top	6.67%	0.00%	0.00%
C.AVG	6.67%	18.73%	0.00%
C.POOR	6.67%	0.00%	0.00%
SW.TOP	6.67%	21.73%	20.53%
SW.AVG	6.67%	0.00%	0.00%
SW.POOR	6.67%	0.00%	0.00%
N.TOP	6.67%	0.00%	0.00%
N.AVG	6.67%	0.00%	0.00%
N.POOR	6.67%	0.00%	0.00%
sum	1	1	1
μ	0.113	0.1167	0.118
σ	0.120	0.114	0.115
μ/σ	0.941	1.024	1.030

In this table, I apply three portfolio strategies (equal weight, minimum-variance, and maximum reward-to-risk ratio portfolios) on different farmland location/qualities in Indiana excluding Southeast region. Equal Wt portfolio strategy is the portfolio formed by giving equal weight to each farmland location/quality. Min Var portfolio is this portfolio formed my minimizing the portfolio risk without constraining the return level. Max Reward-to-Risk ratio portfolio is the portfolio that maximize the ratio of portfolio return to its standard deviation. μ and σ are the portfolio return and standard deviation, respectively. However, I excluded the southeast region.

Table A-II
Alpha and Beta of Minimum-Variance and Maximum Reward-to-Risk Ratio Portfolio

	Min-Var	P-value	Max Reward-to-Risk Ratio	P-value
Alpha α	0.064	0.000	0.064	0.00
Beta β	-0.022	0.82	-0.014	0.88

In this table, I present the Alpha α and Beta β of the minimum-variance portfolio and maximum reward-to-risk ratio portfolio. Min-Var portfolio is this portfolio formed my minimizing the portfolio risk without constraining the return level. Max Reward-to-Risk ratio portfolio is the portfolio that maximize the ratio of portfolio return to its standard deviation.

CHAPTER 3. IS FARMLAND A COMMON RISK FACTOR IN ASSET PRICING MODELS?

Abstract

Farmland represents the largest asset share of the U.S. agricultural balance sheet, accounting for nearly 80% of U.S. farm assets. Motivated by the well-documented real estate risk factor and the similarities between farmland and real estate investing, this chapter examines whether farmland has a risk factor, like real estate, that is affecting asset returns. The proposed farmland risk factor is proxied by the National Council of Real Estate Investment Fiduciaries farmland property index (Farmland NCREIF). Relying on quarterly data from 1991-Q1 to 2016-Q2, we employed the Generalized Method of Moments (GMM) to provide empirical evidence that even though farmland share diversification benefits with like real estate, it fails to be a risk factor to which its exposure affects asset returns. Instead, market frictions and/or non-risk explanations might provide a more plausible description of farmland high risk-adjusted return.

Keywords: Farmland, Risk Factor, Conditional CAPM, Generalized Methods of Moments (GMM), Sharpe Ratio.

3.1 Introduction

The aim of this chapter, as described in its title, is to examine whether farmland exhibits a risk that is compensated with higher return. The primary motivation for this study is the well-documented presence of real estate risk factor (Mei and Lee, 1994; Lee *et al*, 2008; Carmichael and Coën, 2018; among others) in addition to the positive correlation between farmland and real estate (Hardin and Cheng, 2005). Similarities in investment performance between real estate and farmland includes low or negative correlation with stocks and bonds, high correlation with both expected and unexpected inflation, and high risk-adjusted return (Barry, 1980; Irwin et al. 1988; Bjornson & Innes 1992; Hardin and Cheng, 2005; Baker *et al*., 2014). Given the similar investment characteristics of real estate and farmland, I'm asking whether there is a farmland risk factor that explains the cross-section of stocks returns? A positive answer to this question provides support to the risk-based explanations for return. In other words, the high return of farmland investment is due to the high risk associated with it. A negative answer to this question, however, provides support for the non-risk explanation for farmland's high return (i.e., market frictions, irrational investors, and or transactions costs). Put differently, the relatively higher return for farmland is not associated with higher risk.

The favorable farmland investment characteristics noted above might in part justify the recent increase in the institutional investors' acquisition of farmland to be part of their investment portfolio. This trend became blatantly obvious since the large increase in prices of agricultural crops in 2007 along with the 2008 housing bubble and the financial recession (Fairbairn, 2014). As reported by Fu (2013), institutional investors allocated $30 to $40 billion to global farmland. The most conspicuous example of this trend is the $2 billion investment in farmland by the giant pension fund Teachers Insurance and Annuity Association - College Retirement Equities Fund (TIAA-CREF) in 2010 (Fairbairn, 2014). However, given all of that, institutional investors still hold a tiny portion of investable U.S. farmland. Fu (2013) showed that institutional investors hold around 3% to 4% of total U.S. farmland investment, and 7% to 8% of timberland investments. Compare this to U.S. real estate where less than 500 institutional investors hold around 84% of all U.S. real estate investments (Whyte, 2018).

It is intuitive for investors to answer the question: are there factors out there that drive asset prices? Pukthuanthong et al. (2018) pointed to two interesting empirical regularities that show that i) at least one risk factor exists that explains stock returns, and ii) the existence of multiple risk factors. The first point indicates that the lower bound to the volatility of the well diversified portfolio. This suggests that there is at least one risk factor affecting the return of the portfolio constituents (i.e., regardless of how much diversification, volatility still exists). The other empirical regularity is the low correlation between portfolios in different asset classes (e.g., between stocks and bonds, between U.S. stocks and U.K. stocks, or between real estate and stocks). This indicates that there exist multiple risk factors. If there exist only one risk factor (e.g. market risk), we should expect stronger correlation between portfolios across different asset classes.

Early factor tests maintained the hypothesis of constant expected returns. Simply put, expected returns do not vary over time. This is a strong assumption. The logic for varying expected return is that investors ask for more risk premium during recessions and less risk premium during booms. In other words, the marginal utility of consumption is higher in recessions than in booms. Findings are mixed on whether time-varying expected return can help explain the anomalies (e.g., size and value anomalies) that were not explained by constant expected return models, such as the CAPM. For instance, Zhang (2005) showed that time varying expected return could account for the value anomaly. Lewellen and Nagel (2006), on the other hand, pointed out that time variation in expected return did not explain the size and value anomalies. In my analysis, I employ the time-varying expected return method for two reasons. First, if it does not help, it adds no harm. Second, as far as I know, very few studies have adopted the time-varying expected return of farmland investment in their analysis.

Within the farmland market literature, Bjornson (1994) employed the time-varying expected return asset pricing model to capture the predictability of agricultural asset returns. Hanson and Myers (1995) found that the asset pricing model that accounts for time-varying expected return is more successful in pricing farmland than a present value model that assumes constant risk premium. In order to account for time variations in expected return, I used the latent multifactor asset pricing model. Conditional betas are estimated with the generalized method of moments (GMMs). Instruments are needed for the latent multifactor asset pricing model to account for time variation in expected return. The instruments we used are the lagged default premium, lagged term premium, and Shiller Cyclically Adjusted Price Earnings ratio (CAPE) index.

Contemporary asset pricing literature remains in search for empirically relevant fairly priced factors that exhibit explanatory power for expected stock returns across a wide range of portfolio styles. I use this "risk factor" approach to examine whether farmland has a role in explaining asset pricing and present evidence that there is no farmland risk factor. Findings suggest that even though farmland has a high risk-adjusted return relative to the market portfolio, there is no risk relationship between farmland and stock return. So, exposure to farmland risk has no influence on asset returns. Having no risk relationship between farmland and financial market does not imply that farmland is not attractive to investors. It implies instead that there is abnormal profit associated with farmland investment. By "abnormal" I mean that it is not explained by the efficient market theory and the resulting risk-based analysis of risk adjusted return of farmland. Why are institutional investors reluctant to make the abnormal profit associated with these anomalies? A massive literature in financial economics has attempted to answer this question. Shleifer and Vishny (1997), for instance, argued that betting heavily on these anomalies might be dangerous since these anomalies might even grow in the future leading to poorer return on investment.

Lewellen (2011) found that the aggregate holdings of institutional investors are very close to the market portfolio. They did not take advantage of these market anomalies.

This chapter contributes to the massive literature on explaining the cross-section of expected stock returns. The closest study to ours is Carmichael and Coen (2018) which found that there is real estate risk factor with the U.S. stock market. To the best of my knowledge, I'm the first to empirically examine a farmland risk factor and its effect on common stocks' returns. In addition, my findings add more insight to the reluctance of institutional investors to invest in farmland.

The rest of this chapter is organized as follows. Section 3.2 discusses the related literature highlighting the exogenous and endogenous approaches to factor risk pricing. Section 3.3 describes the methodology and econometric model. Data description and sources will be discussed in section 3.4. Sections 3.5 and 3.6 present the empirical results and conclusions, respectively.

3.2 Literature Review

This chapter integrates and contributes to two strands of literature. First, it is related to the growing body of studies examining the investment performance of farmland (e.g., Barry, 1980; Irwin et al., 1988; Bjornson & Innes, 1992; Baker et al., 2014). In this literature, return and risk characteristics of farmland are examined. In particular, the focus has been on how the risk and return of well-diversified portfolio change as a result of adding farmland to it. Barry (1980) used CAPM to estimate the systematic risk of farmland. Irwin et al. (1988) extended Barry's sample and added the inflation factor to the CAPM's market factor. Both studies found that farmland adds very little risk to a well-diversified portfolio (relatively low β). Bjornson & Innes (1992) found that the returns to investing (as opposed to operating) agricultural assets provide more risk-adjusted return than investing in non-agricultural assets. Baker et al. (2014) showed that, in addition to the low beta (β), farmland is also a good hedge to both expected and unexpected inflation. I extend this line of literature by documenting whether this performance has a risk relationship to the U.S. stock market

I integrate this farmland attractiveness strand to another line of the financial economics literature that examines how factors influence the cross-section of stock returns. Extant literature has focused on two approaches when studying whether a candidate factor is significant in predicting the cross-section of stock returns. The first relies on the integration/segmentation of the proposed factor or asset with the stock market. We might call this approach the "endogenous approach to factor pricing." The intuition behind this approach is that determining whether or not a certain asset class (or certain market) has a positive risk premium is related to whether this asset or market is integrated or segmented from the capital market. If the two markets are integrated, then the same factors explain the returns of both markets. Segmented markets, however, suggest that risk factors that explain one of the markets cannot explain the other. Super risk premium is generally associated with segmented markets. Accordingly, from a factor investing perspective, in order to get exposure to this risk and get this risk premium, the investor should incorporate these segmented assets that have positive risk premium into his/her portfolio. In other words, since factor investing entails diversifying across factors instead of diversifying across assets, factors that have positive risk premium should be part of a well-diversified portfolio.

The first empirical test of integration vs. segmentation was by Stehle (1977) who tested the segmentation of the U.S. stock market relative to the world market. Attempts prior to Stehle (1977) looked at whether assets are priced in segmented (integrated) markets against the null of no relationship. Stehle (1977) was the first to simultaneously test the segmentation vs. integration hypothesis. He used the Fama-McBeth cross-sectional, time series approach to test the integration vs. segmentation hypothesis. The low power of the Fama-McBeth regression motivated Jorion and Schwartz (1986) to use the maximum likelihood approach since it has more power than the Fama-McBeth regression. They aimed to study integration vs. segmentation of the Canadian stock market relative to the global North American market. Their results show that integration is rejected which indicate that some segmentation might exist between the Canadian equity market and the global North American equity market. This segmentation indicates that risk exposure to the global North American market is not priced in the Canadian stock market. This study set the stage for other segmentation vs. integration studies with different geographic focus like Mexico (Domowitz et al., 1998) and U.K (Taylor and Tonks, 1989).

The second strand of literature considers assets, markets, or characteristics to be exogenous factors, rather than being affected by other factors. Even though this literature is massive,[2] previous studies have not examined whether farm real estate can be regarded as a risk factor that is rewarded in the stock market. The closest studies to ours is literature that has examined oil and real estate as risk factors. Chen et al. (1986) investigated the impact of oil price changes on U.S. stock market and found the effect to not be significant. Ferson and Harvey (1994) examined oil price changes as a risk factor at the global level. They also found that there is no significant risk premium for oil price changes. With respect to real estate, Liu et al. (1990) found that commercial real estate is segmented from the stock market and has a super risk premium associated with it. Mei and Lee (1994) showed that in addition to market and bond factors, there exist a real estate factor in pricing capital assets. Using the latent variable asset pricing model, Carmichael and Coen (2018) showed the presence of a real estate factor in explaining the cross-section of stock returns. My work extends Carmichael and Coen's work by examining the presence of a farmland factor in predicting the cross-section of stock returns.

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[2] Harvey et al. (2016) have listed 316 factors that are suggested in 313 papers in top journals in finance, economics, and accounting from 2006 to 2016.

Screening the two approaches discussed above (the endogenous and exogenous approaches to factor pricing), the only study that conducted a formal test of segmentation vs. integration of farmland was a study by Shiha and Chavas (1995). As they were motivated by the failure of the standard CAPM to explain farmland prices, they examined the segmentation of farmland market from financial markets. Their findings, as expected, indicated that the farmland market was economically and statistically segmented from the financial market. A modified CAPM that incorporated market imperfections did a better job explaining farmland prices.

In summary, with respect to the massive literature on the factors and the pricing of the cross-section of expected assets' returns, there is no study that has examined whether farmland could be a potential risk factor. In this study, I fill this gap by examining the potential role of farmland in the cross-section of assets' returns. In doing so, I choose the exogenous approach to factor pricing.

3.3 Methodology

In this section, I describe the latent variable asset pricing model and the econometric estimation of the model parameters.[3] The descriptions of the latent-variable asset pricing model and the econometric procedures are based on Ferson (1990) and Gibbons and Ferson (1985).

Let R_{t+1} be a column vector of N excess return of N assets (or portfolios) at time $t+1$. Let K be the factor innovations or state variable in the economy. The absence of arbitrage in the economy implies that

$$E_t(R_{t+1}) = \beta \lambda_t \quad (1)$$

[3] For a detailed discussion related to latent variable asset pricing model, the reader is advised to read Ferson (1990).

where λ_t is the vector of K risk premiums at time t, and β is N×K matrix of factor loadings. Note that in Eq (1) the factor loadings are invariant to time while the risk premiums are time variant.

Partition the N excess returns into two groups, namely reference and test assets. That is $R_{t+1} = \begin{pmatrix} R_{t+1}^{I} \\ R_{t+1}^{II} \end{pmatrix}$ where R_{t+1}^{I} and R_{t+1}^{II} are the excess returns of reference and test assets, respectively. The number of reference assets should be the same as the number of the factor innovations, K. Therefore, R_{t+1}^{I} is a vector of K excess returns while R_{t+1}^{II} is a vector of N-K excess returns. The β matrix is set up so that excess returns can be partitioned. That is $\beta = \begin{pmatrix} \beta_I \\ \beta_{II} \end{pmatrix}$ where β_I is a K×K matrix and β_{II} is N-K× K.

Based on this partition, Eq (1) is partitioned accordingly

$$E_t\,(R_{t+1}^{I}) = \beta_I\,\lambda_t \qquad (2)$$

$$E_t\,(R_{t+1}^{II}) = \beta_{II}\,\lambda_t \qquad (3)$$

The restriction on the relationship between the reference and test asset can be obtained by solving Eq (2) for λ_t and plugging it back into Eq (3)

$$E_t\,(R_{t+1}^{II}) = \beta_{II}\,\beta_I^{-1}\,E_t\,(R_{t+1}^{I}) \qquad (4)$$

Based on Eq (4), reference assets are used to price the test assets.

To model the factor innovations, a linear relationship is often assumed to describe the relationship between the information set Z_t and the factor innovations f_{t+1}

$$F_{t+1} = \phi_0 + \phi_1 Z_t + f_{t+1} \tag{5}$$

where ϕ_0 and ϕ_1 are vectors of K intercepts and a K×K matrix of coefficients, respectively. Following the same assumption, the reference asset return is assumed to be as follows:

$$E_t\,(R^I_{t+1}) = \varphi_0 + \varphi_1 Z_t \tag{6}$$

Combining Eqs (1-6) with the multifactor asset pricing model results in the following:

$$R_{t+1} = E_t\,(R\ t{+}1) + \beta f_{t+1} + \alpha_{t+1} \tag{7}$$

where α_{t+1} is the abnormal return (return not described by the pricing model). Subsequently, we end up with the following system of equations:

$$F_{t+1} - \phi_0 - \phi_1 Z_t = f_{t+1} \tag{8}$$

$$R^I_{t+1} - (\varphi_0 + \varphi_1 Z_t) - \beta_I\,(F_{t+1} - \phi_0 - \phi_1 Z_t) = \alpha^I_{t+1} \tag{9}$$

$$R^{II}_{t+1} - \beta_{II}\,\beta_I^{-1}\,(\varphi_0 + \varphi_1 Z_t) - \beta_{II}(F_{t+1} - \phi_0 - \phi_1 Z_t) = \alpha^{II}_{t+1} \tag{10}$$

Eq (8) is the regression of the factors' returns F_{t+1} on the state variables Z_t. Therefore, this equation identifies the unanticipated (unexplained) part of state variables f_{t+1}. Eq (9) is the regression of the K reference assets' excess returns on the unexplained part of the state variables (f_{t+1}) which gives us the beta coefficients, β_I, of the reference assets. This regression produces the unexplained excess returns on the K reference assets α^I_{t+1}. Then, the unexplained portion of the excess return of the K-N test assets (α_{t+1}^{II}) is identified in eq (10) and the beta coefficients of the test assets (β_{II}) are estimated.

Based on the system 8 – 10, the excess returns of reference and test assets are linked by their conditional betas. The parameters in the system 8 – 10 are estimated by the Generalized Method of Moments (GMM) proposed by Hansen (1982). GMM does not impose distributional assumptions on the residuals. In other words, it allows for serial correlation and/or heteroskedasticity of the error term. GMM is regarded as a more general model than OLS and GLS. I'm using Hansen's J_T statistic to evaluate the model's overidentifying restrictions. Hansen's J_T statistic is a valid test statistic when the weighting matrix is the inverse of covariance matrix of the moment conditions. That is why I use Hansen's J_T statistic with the two-step GMM estimation.

3.4 Data

I proxy farmland return with the National Council of Real Estate Investment Fiduciaries (NCREIF) farmland property index. Specifically, I use NCREIF's quarterly observations from 1991-Q1 to 2016-Q2. NCREIF is an index of return on farmland privately held by tax-exempt institutional investors like pension funds. The valuations of farmland properties included in the index represent appraisals rather than actual transaction prices. Even though there are many problems associated with appraisal data (i.e., appraisal bias), transaction data for farmland could be more problematic given the thinness of farmland market.[4]

[4] Bigelow *et al.* (2016) estimated that annually less than 4% of U.S. farmland changed hands over the period 2015- 2019.

I combine NCREIF data with quarterly data on the value weighted return of the Center for Research in Security Prices (CRSP) firms in the U.S., and stock market data from Kenneth French's website. These data include the excess market returns and ten decile Fama-French size portfolios. The excess return on the market is the value-weighted return of all U.S. CRSP firms that are listed in NYSE, AMEX, and NASDAQ and have CRSP code of 10 or 11 at the beginning of quarter t. Size portfolios are constructed by grouping stocks based on their market equity (stock price multiplied by shares outstanding). The standard approach for detecting risk factors as proposed by Fama and French is i) sorting assets into portfolios according to certain characteristics (in my case this characteristic is size), ii) estimating the average return of each characteristic portfolio, iii) regressing the characteristic portfolios on the candidate factor or factors, and iv) looking at the pattern of mean returns and the pattern of the portfolio betas to see if there is correspondence between them (i.e., whether higher beta is corresponding to higher average return). In order to calculate the excess return on the decile portfolios, the one-month T-bill rate is subtracted from each decile portfolio. To match the farmland NCREIF index, I converted these data from monthly to quarterly by averaging the monthly observations for each quarter.

I relied on three instruments to estimate the conditional asset pricing model. They are the default premium, term premium, and Shiller's cyclically adjusted price-earnings ratio (CAPE). The default premium is the difference between Moody's Baa and Aaa corporate bond yields. The term premium is the difference between the 10-year government bond and the one-month treasury bill. Data to calculate default and term premium is obtained from the Federal Reserve Bank of St-Louis's FRED economic database. CAPE is obtained from Robert Shiller's website. I followed Carmichael and Coen (2018) in adjusting Shiller's CAPE ratio by taking the first difference of its log. The instruments described above are widely used in the financial economics literature in forecasting future stocks and bonds returns (Ferson, 1990).

3.5 Empirical Results

In this chapter, I study the hypothesis that a factor pricing model holds; namely, that farmland returns along with the market return are factors that help explain asset returns. More formally, a farmland return factor pricing model says there exist a discount factor that is a function of the farmland returns and the market factor and yet helps price assets.

With farmland as a potential risk factor, this section shows the results of estimating the system of equations 8 – 10. Since the market factor is common across many asset pricing models, I examined an asset pricing model that incorporates the market factor and the farmland factor. Motivated by previous literature, the instruments Z_t used to predict returns are the constant term, the lagged excess market return, the lagged farmland return, the lagged default premium, the lagged term premium, and the lagged Shiller's CAPE index. The incorporation of lagged market return as an instrument is primarily motivated by Ferson (1990) and is also used by Carmichael and Coen (2018). The common argument for using lagged market as an instrument is to capture the mean reversion of the expected returns to their long term mean. Put differently, if returns are lower than the long-term average return, the expected return will be higher than average.

Before showing the empirical results, it might be useful to look at the summary statistics of the factors, instruments, and the portfolios. This is shown in table 3.1. Over the period 1991 – 2016, the farmland factor (measured by farmland NCREIF) has higher average quarter return (3%) than the return of the value weighted market index MKT (2%), corresponding to 12% for farmland and 8% for the market on an annual basis. The volatility of the market factor is higher than that of the farmland factor (8% and 3% for market and farmland, respectively). The well-documented size effect is also apparent in table 1. The portfolio return declines as size increases. The return on the smallest size portfolio, R_1, is 3.2% and the return of largest size portfolio, R_{10}, is 2.2%. The size effect also involves declining volatility as size increases. The volatility of the low size portfolio is 11.8%, while it is 7.8% for the largest size portfolio. The reason I focus on portfolios rather than individual stocks is that using an aggregate return reduces noise and delivers more precise estimates of the model parameters. The first and second order autocorrelation are high for the default premium and term premium which indicate more persistence compared to the factors and portfolios.

Table 3.1 : Summary Statistics: Quarterly Data, 1991: Q1 - 2016: Q2

	Mean (Quarterly)	St. Dev	Min	Max	ρ_1	ρ_2
MKT	0.020	0.081	-0.224	0.207	0.040	0.031
F_NCREIF	0.029	0.031	0.000	0.228	-0.011	0.054
R_1	0.032	0.118	-0.310	0.317	0.067	-0.090
R_2	0.030	0.116	-0.257	0.320	-0.091	-0.003
R_3	0.031	0.108	-0.275	0.246	-0.106	-0.047
R_4	0.028	0.102	-0.256	0.263	-0.147	-0.026
R_5	0.029	0.102	-0.274	0.249	-0.079	-0.035
R_6	0.030	0.094	-0.220	0.234	-0.062	-0.042
R_7	0.030	0.095	-0.273	0.255	-0.011	0.013
R_8	0.030	0.093	-0.249	0.227	-0.040	0.021
R_9	0.028	0.084	-0.275	0.212	0.036	-0.048
R_{10}	0.022	0.078	-0.198	0.229	0.089	0.093
DF	0.961	0.414	0.550	3.380	0.801	0.549
S	0.043	0.019	0.004	0.085	0.980	0.950
P/E	0.004	0.073	-0.281	0.207	0.157	0.015

This table presents the mean, standard deviation, maximum, minimum, and the first ρ_1 and ρ_2 second order autocorrelation coefficients of factors, size portfolios, and instruments. The factors are the market MKT, and the farmland National Council of Real Estate Investment Fiduciaries (F_NCREIF) index. R_i is the excess return on the i^{th} portfolio decile portfolio formed based on market equity. Within each decile, a value weighted portfolio is formed. The risk-free rate is based on 3-month T-bills. Instruments used are the default premium DF, the term premium S, and Shiller's cyclically adjusted price earnings ratio P_E.

Figure 3.1 shows the quarterly times series of the market portfolio and the F_NCREIF index. The Pearson correlation coefficient between the market portfolio and F_NCREIF is 13%. This low correlation indicates that farmland return is quite different from the market return. Regarded as an estimate for the relationship between expected return and volatility, the Sharpe ratio is calculated by dividing the return in excess of 3-month treasury bills over the standard deviation of return. Summary statistics reveal that F_NCREIF has the highest Sharpe ratio (0.87) among all portfolios and the market index. The 3-month treasury bill rate over the period is 0.002. The Sharpe ratio for the market excess return over the same period is 0.22.

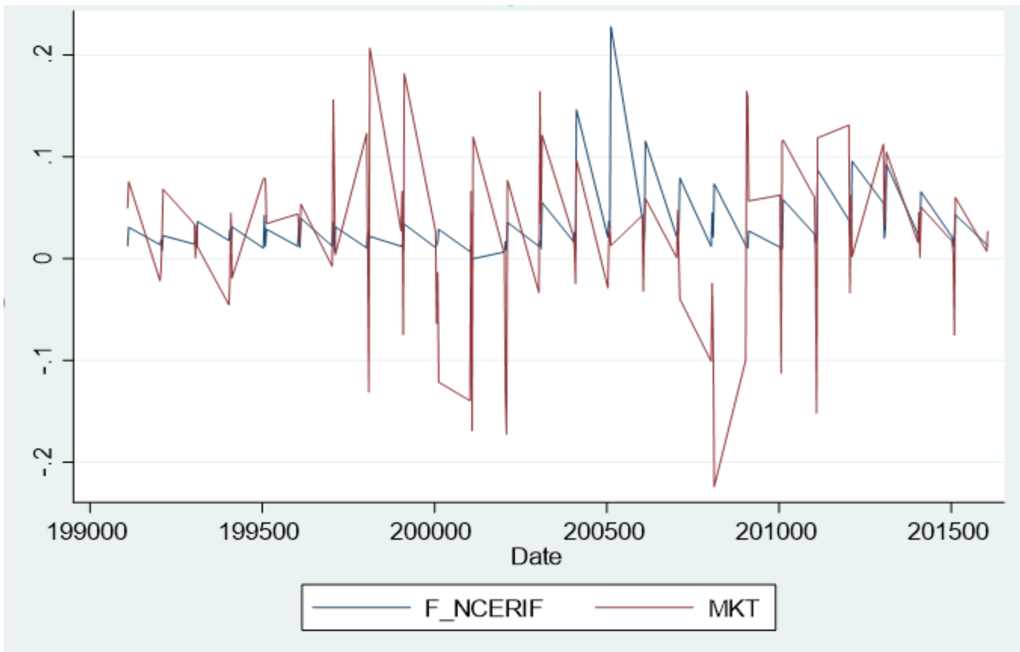

Figure 3.1: Quarterly Time Series of Farmland NCREIF and Market Portfolio (1990-2016)

Being an appraisal-based index, NCREIF suffers from a critical shortcoming resulting from using survey data. It is a smoothed return series. In other words, return or price observations are autocorrelated. There has been considerable debate in the literature concerning the use of statistical techniques to desmooth time series. Geltner (1993) and Getmansky et al. (2004), among others, proposed statistical and econometrical methods to estimate market values from appraised values. However, Cheng et al. (2011) showed that the heterogeneity of the appraisers could eliminate this appraisal bias.

In this study, I adopted the second view. The reason for this choice is twofold. First, the autocorrelation coefficient for farmland NCREIF is very low. The first and second order autocorrelations coefficients for farmland NCREIF are -0.011 and 0.054, respectively. It is noteworthy to compare this weak autocorrelation coefficients for farmland NCREIF with the real estate property NCREIF of 0.80 over the same period with the same frequency. This strong positive autocorrelation coefficient of real estate NCREIF motivated Carmichael and Coen (2018) to desmooth this return series using Getmansky et al. (2004). Second, buyers (sellers) in farmland markets rely on these survey data to make their buying (selling) decisions. Therefore, we can argue that transaction prices are guided by these survey data.

Table 3.2 reports the GMM estimates of the system of equations 8 – 10 with farmland as a risk factor along with the market risk factor. The farmland risk factor is proxied by farmland F_NCREIF. Estimation of the parameters is based on the period 1991 Q1 to 2016 Q2. I used deciles 1 and 5 as reference portfolios. Ferson (1990) showed that even though the choice of reference and test assets might affect the ease of computations, the parameters' estimates are not sensitive to this choice. The remaining eight size portfolios are used as test assets. In addition to the joint parameters estimates for three blocks of equations 8 – 10, table 2 presents the factor equations, the reference assets equations, and the test assets equations.

As shown in the first and second parts of table 3.2, not all instruments are statistically significant in predicting factor return. However, as argued by Ferson (1990), getting the best prediction for each equation is cumbersome process. In addition, overfitting and data mining are more likely in this case. Also, these instruments are widely used in asset pricing literature. The third part of table 2 reports the beta estimates for the market factor and farmland factor. It is expected that the beta of the stock's portfolios with respect to the market will be close to 1 since the portfolio and the market value weighted stock portfolio are in the same universe of stocks. My results confirm such expectation. Size portfolio market betas range from 0.94 for the largest size portfolio to 1.23 for the second decile portfolio. The t-statistics are quite large, ranging from 14.57 to 48.75.

For the farmland risk factor, estimates are neither statistically nor economically significant. The portfolios betas with respect to farmland are all around zero with t-statistics ranging from 0.21 to 0.62. They are all below the threshold t-value of 3 suggested by Harvey et al. (2016). This threshold corresponds to p-value of 0.0027. Harvey et al. (2016) suggested this hurdle rate with an aim for lowering the possibility of data mining and false factor discoveries. Using this hurdle rate, many of the factors in prior studies are deemed insignificant. This model has a Hansen J_T statistic of 39.80 with associated p-value of 0.7943, suggesting that this two factor ICAPM provides a good specification of risk embodied in the data. However, the t-values of the factors imply that most of the risk effect of the factors is borne by the market factor, not the farmland factor. I cannot reject the null hypothesis at the 5% level that the model is well specified. In other words, the model provides a good description for the relationship between risk factors and the assets' expected returns.

Table 3.2: The Two Factor ICAPM (1991:Q1 - 2016:Q2) - Value-Weighted Portfolios

$J_T = 39.80$ P-Value = 0.7943

	cst	Lag_mkt	Lag_fm	def_prem	Spread	P/E
$R_{f,t+1}$	0.057	-0.023	-0.001	-0.011	-0.455	-0.014
	(3.63)	(0.24)	(0.01)	(1.13)	(2.08)	(0.13)
$R_{m,t+1}$	0.043	-0.376	-0.170	0.000	-0.286	0.523
	(1.03)	(1.49)	(0.65)	(0.01)	(0.49)	(1.83)

	cst	Lag_mkt	Lag_fm	def_prem	Spread	P/E
$R_{1,t+1}$	-0.031	0.135	-0.047	0.034	0.726	0.136
	(0.55)	(0.39)	(0.14)	(1.15)	(0.96)	(0.36)
$R_{5,t+1}$	0.038	-0.386	-0.153	0.002	0.003	0.551
	(0.76)	(1.25)	(0.50)	(0.08)	(0.00)	(1.60)

	$\beta_{j,1}$	$\beta_{j,2}$	$\beta_{j,3}$	$\beta_{j,4}$	$\beta_{j,5}$	$\beta_{j,6}$	$\beta_{j,7}$	$\beta_{j,8}$	$\beta_{j,9}$	$\beta_{j,10}$
$f_{f,t+1}$	0.000	-0.011	-0.012	-0.014	-0.013	-0.011	-0.011	-0.013	-0.010	-0.013
	(0.21)	(0.62)	(0.62)	(0.62)	(0.62)	(0.62)	(0.62)	(0.62)	(0.62)	(0.62)
$f_{m,t+1}$	1.18	1.23	1.19	1.14	1.18	1.09	1.12	1.11	1.02	0.936
	(14.57)	(17.71)	(21.12)	(23.32)	(27.53)	(27.86)	(31.83)	(33.40)	(40.40)	(48.75)

This table presents the GMM estimates of the system:

$F_{t+1} - \phi_0 - \phi_1 Z_t = f_{t+1}$

$R^I_{t+1} - (\varphi_0 + \varphi_1 Z_t) - \beta_I (F_{t+1} - \phi_0 - \phi_1 Z_t) = \alpha^I_{t+1}$

$R^{II}_{t+1} - \beta_{II} \beta_I^{-1} (\varphi_0 + \varphi_1 Z_t) - \beta_{II}(F_{t+1} - \phi_0 - \phi_1 Z_t) = \alpha^{II}_{t+1}$

The first part reports the coefficients of the instruments for both the farmland factor ($R_{f,t+1}$) and the market factor ($R_{m,t+1}$). These instruments are the constant (cst), the lagged market return (lag_mkt), the lagged farmland return (lag_fm), the lagged default premium (def_prem), the lagged yield (spread), and the lagged price/earnings ratio (P/E). The second part reports the coefficients of the instruments for the two reference portfolios. They are the excess returns of portfolios of size 1 and 5. The third part reports the factors' betas $\beta_{i,j}$ for each portfolio (the beta of portfolio i with respect to factor j). The t-values are in the parenthesis. J_T is the Hansen's statistic to measure the over-identifying restriction of the model.

To gauge the robustness of my results across different portfolios, I repeat the analysis using equal-weighted size portfolios. Within each size decile, an equal-weighted portfolio is formed. Table 3.3 reports summary statistics and table 3.4 reports the estimation results for equal weighted portfolios. Generally speaking, the results are quite similar to those in table 3.2. The market beta ranges from 1.02 to 1.29 with t-statistics ranging from 12.30 to 43.38. The farmland factor betas are a little higher for the equal-weighted portfolio compared to the value-weighted size portfolios. However, they are also economically and statistically indistinguishable from zero. Their t-statistics range from 0.05 to 0.94. The Hansen J_T statistic is 47.07 with a corresponding p-

Table 3.3: Summary Statistics (Equal-Weighted Portfolios): Quarterly Data, 1991:Q1 - 2016:Q2

	Mean (Quarterly)	**St. Dev**	**Min**	**Max**
$\mathbf{R_1}$	0.039	0.133	-0.337	0.441
$\mathbf{R_2}$	0.029	0.124	-0.283	0.378
$\mathbf{R_3}$	0.030	0.115	-0.290	0.381
$\mathbf{R_4}$	0.028	0.111	-0.273	0.335
$\mathbf{R_5}$	0.030	0.112	-0.294	0.349
$\mathbf{R_6}$	0.031	0.103	-0.243	0.299
$\mathbf{R_7}$	0.030	0.103	-0.288	0.302
$\mathbf{R_8}$	0.030	0.010	-0.267	0.276
$\mathbf{R_9}$	0.029	0.091	-0.286	0.314
$\mathbf{R_{10}}$	0.023	0.084	-0.221	0.215

This table presents the mean, standard deviation, maximum, and minimum of excess returns of equal-weighted size portfolios. R_i is the excess return on the i^{th} decile portfolio formed based on market equity. Within each decile, an equal-weighted portfolio is formed. The risk-free rate is based on 3-month T-bills.

value of 0.5108, suggesting that I cannot reject the null hypothesis at the 5% level that the model is well specified.

Since F_NCREIF is an appraisal-based index, my estimates of average returns and volatility may suffer from appraisal bias. As shown in the beginning of this section, F_NCREIF has very low first and second order serial correlation. Geltner (1993) proposed a desmoothing equation that does not depend on autocorrelation. As an additional check on the robustness of results, I desmoothed the F_NCREIF index using the following equation:

$$r_t^u = (r_t^a - (1 - M)r_{t-1}^a)/M \tag{11}$$

where r_t^u is the unsmoothed true return at time t, r_t^a and r_{t-1}^a are the observed appraised return at times t and t-1, respectively, and M is the appraisers' confidence factor. Geltner (1993) argued

Table 3.4: The two Factors ICAPM (1991:Q1 - 2016:Q2) - Equal-Weighted Portfolios

J_T = 47.07	p-Value = 0.5108					
	cst	Lag_mkt	Lag_fm	def_prem	Spread	P/E
$R_{f,t+1}$	0.057	-0.015	0.011	-0.010	-0.449	-0.029
	(3.65)	(0.16)	(0.11)	(1.21)	(2.07)	(0.28)
$R_{m,t+1}$	0.039	-0.414	-0.135	0.003	-0.270	0.567
	(0.92)	(1.65)	(0.52)	(0.15)	(0.46)	(1.98)
	cst	Lag_mkt	Lag_fm	def_prem	Spread	P/E
$R_{1,t+1}$	-0.104	0.376	0.143	0.072	1.55	-0.069
	(1.68)	(1.00)	(0.39)	(2.20)	(1.82)	(0.17)
$R_{5,t+1}$	0.017	-0.451	-0.075	0.021	0.093	0.615
	(0.30)	(1.34)	(0.22)	(0.69)	(0.12)	(1.62)

	$\beta_{j,1}$	$\beta_{j,2}$	$\beta_{j,3}$	$\beta_{j,4}$	$\beta_{j,5}$	$\beta_{j,6}$	$\beta_{j,7}$	$\beta_{j,8}$	$\beta_{j,9}$	$\beta_{j,10}$
$f_{f,t+1}$	0.00	-0.40	-0.047	-0.050	-0.048	-0.043	-0.042	-0.046	-0.039	-0.043
	(0.05)	(0.93)	(0.93)	(0.94)	(0.94)	(0.94)	(0.94)	(0.94)	(0.94)	(0.94)
$f_{m,t+1}$	1.22	1.29	1.28	1.25	1.28	1.19	1.21	1.19	1.10	1.02
	(12.30)	(16.73)	(20.36)	(22.40)	(25.56)	(26.18)	(30.69)	(33.07)	(35.48)	(43.38)

This table presents the GMM estimates of the system:

$F_{t+1} - \phi_0 - \phi_1 Z_t = f_{t+1}$

$R^{I}_{t+1} - (\varphi_0 + \varphi_1 Z_t) - \beta_I\,(F_{t+1} - \phi_0 - \phi_1 Z_t) = \alpha^{I}_{t+1}$

$R^{II}_{t+1} - \beta_{II}\,\beta_I^{-1}\,(\varphi_0 + \varphi_1 Z_t) - \beta_{II}(F_{t+1} - \phi_0 - \phi_1 Z_t) = \alpha^{II}_{t+1}$

The first part reports the coefficients of the instruments for both farmland factor ($R_{f,t+1}$) and market factor ($R_{m,t+1}$). These instruments are the constant (cst), the lagged market return (lag_mkt), the lagged farmland return (lag_fm), the lagged default premium (def_prem), the lagged yield (spread), and the lagged price/earnings ratio (P/E). The second part reports the coefficients of the instruments for the two reference portfolios. They are the excess returns of portfolios of size 1 and 5. The third part reports the factors' betas $\beta_{i,j}$ for each portfolio (the beta of portfolio i with respect to factor j). The t-values are in the parenthesis. J_T is the Hansen's statistic to measure the over-identifying restriction of the model.

that M is approximately 0.40 for real estate assets. So, I also adopted this value for M. Table 3.5 shows the estimation results after desmoothing the F_NCREIF series. The results are generally not different from the previous analysis.

Going back to table 3.1, descriptive statistics show that farmland has a superior Sharpe ratio relative to the market factor. However, the rest of my analysis reveals that it has no risk relationship with asset prices. This is similar to a study by Charoenrook and Conrad (2005) who found that a liquidity factor had a higher Sharpe ratio than the value-weighted market portfolio. This liquidity factor was higher than the plausible upper bound of the Sharpe ratio suggested by MacKinlay (1995) of 0.6. Charoenrook and Conrad suggested that more work has to be uncovered for risk-based explanations to explain the liquidity factor. Pukthuanthong et al. (2018) proposed a protocol that includes testing whether the Sharpe ratio of the candidate factor statistically exceeds the bound suggested by MacKinlay (1995). According to Pukthuanthong et al. (2018), a Sharpe ratio that is significantly higher than the bound proposed by MacKinlay (1995) provides evidence against a risk-based explanation of a factor premium. In other words, in an efficient market where investors are rational, it is not common to see a relatively high Sharpe ratio. When there is an asset or a strategy that yields a high Sharpe ratio, non-risk models that include behavioral economics and market frictions may provide a potential explanation for it. With a Sharpe ratio higher than this reasonable bound, we can also argue that this is evidence against a risk-based explanation of the existence of a farmland factor premium.

Table 3.5: The Two Factor ICAPM (1991:Q1 - 2016:Q2) - Value-Weighted Portfolios with a desmoothed F_NCREIF Index

J_T = 38.81					p-Value = 0.8255					
	$\beta_{j,1}$	$\beta_{j,2}$	$\beta_{j,3}$	$\beta_{j,4}$	$\beta_{j,5}$	$\beta_{j,6}$	$\beta_{j,7}$	$\beta_{j,8}$	$\beta_{j,9}$	$\beta_{j,10}$
$f_{f,t+1}$	-0.018	-0.004	-0.006	-0.007	-0.032	-0.004	-0.004	-0.007	-0.003	-0.007
	(0.44)	(0.28)	(0.55)	(0.75)	(1.62)	(0.34)	(0.34)	(0.71)	(0.26)	(0.80)
$f_{m,t+1}$	1.18	1.23	1.19	1.14	1.18	1.09	1.12	1.10	1.02	0.93
	(14.69)	(17.67)	(21.12)	(23.25)	(25.92)	(27.97)	(31.54)	(33.27)	(39.77)	(49.07)

This table presents the GMM estimates of the system:

$F_{t+1} - \phi_0 - \phi_1 Z_t = f_{t+1}$

$R^{I}_{t+1} - (\varphi_0 + \varphi_1 Z_t) - \beta_I (F_{t+1} - \phi_0 - \phi_1 Z_t) = \alpha^{I}_{t+1}$

$R^{II}_{t+1} - \beta_{II}\, \beta_I^{-1} (\varphi_0 + \varphi_1 Z_t) - \beta_{II}(F_{t+1} - \phi_0 - \phi_1 Z_t) = \alpha^{II}_{t+1}$

The estimates of the coefficients for the instruments and the reference assets are not shown to preserve space. So in this table I only report the factors' betas $\beta_{i,j}$ for each portfolio (the beta of portfolio i with respect to factor j). The t-values are in the parenthesis. J_T is the Hansen's statistic to measure the over-identifying restriction of the model. F_NCREIF is desmoothed using methodology of Geltner (1993).

3.6 Conclusions

In this chapter, I showed that exposure to farmland risk has neither economical nor statistical explanatory power for the expected returns across a range of equity portfolios. Unlike real estate, farmland has no common risk factor in the cross section of assets return. These results hold for both value-weighted and equal-weighted size portfolios. My findings do not suggest that farmland is not an interesting asset class to institutional investors. Investors still can benefit from the abnormal return associated with farmland investment which is not explained by the asset pricing model. What I have shown in this chapter is that farmland is not a priced risk factor from a risk-based perspective. In other words, risk-based explanations indicate that farmland is a free lunch in the sense that its premium is not associated with risk. Other possibilities might include a risk-based explanation with market frictions such as transaction costs and taxes. CAPM and factor pricing models assume that markets are frictionless (i.e., perfect markets). Studies have shown that these frictions can have a significant impact on pricing assets. For example, Shiha and Chavas (1995) suggested that barriers to flow of funds from non-agricultural to the agricultural sectors indicates why non-agricultural investors do not exploit the profitable opportunities in agriculture (i.e., high Sharpe ratio). Moreover, non-risk-based analysis might provide explanations for farmland return. An example of non-risk explanations is the presence of irrational behavior. Irrational behavior suggest that investors may, for example, irrationally extrapolate past returns growth rates into the future. This would lead to a trend in asset returns (in violation of efficient market hypothesis which assumes asset returns are unpredictable from past returns).

There are limitations to my framework. First, because the farmland NCREIF index started in the first quarter of 1991, the time period I used was relatively short. Second, measurement errors pose a limitation for any study that examines farmland data. As farmland values and cash rent data are collected from surveys, they may not reflect fundamental values. I think that farmland real estate investment trusts (farmland REITs) solve a lot of the measurement problems. However, farmland REITs started in 2014, resulting in a limited time series. Future research could use farmland REITs to explore whether farmland risk is priced in asset markets. Third, as farmland NCREIF tracks the farmland held by institutional investors, it might not be representative of the whole farmland market. Fourth, farmland return data are obtained from appraisals, not actual transactions. Obtaining transaction date is very challenging given the thinness of the farmland market. Approximately 2% of U.S. farmland changes hands in a given year (Burns et al., 2018).

3.7 References

Baker, T. G., Boehlje, M. D., & Langemeier, M. R. (2014). Farmland: is it currently priced as an attractive investment? *American Journal of Agricultural Economics*, 96(5), 1321-1333.

Barry, P. J. (1980). Capital asset pricing and farm real estate. *American Journal of Agricultural Economics*, 62(3), 549-553.

Bigelow, D., Borchers, A., & Hubbs, T. (2016). US farmland ownership, tenure, and transfer , EIB-161, U.S. Department of Agriculture, Economic Research Service.

Bjornson, B. (1994). Asset pricing theory and the predictable variation in agricultural asset returns. *American Journal of Agricultural Economics*, 76(3), 454-464.

Bjornson, B., and Innes, R. (1992). Another look at returns to agricultural and nonagricultural assets. *American Journal of Agricultural Economics*, 74(1), 109-119.

Burns, C., Key, N., Tulman, S., Borchers, A., and Weber, J. (2018). *Farmland values, land ownership, and returns to farmland*, 2000-2016, ERR-245, U.S. Department of Agriculture, Economic Research Service.

Carmichael, B., and Coën, A. (2018). Real estate and consumption growth as common risk factors in asset pricing models. *Real Estate Economics*, *46*(4), 936-970.

Charoenrook, A.A., and Conrad, J.S. (2005, June). Identifying risk-based factors. In AFA 2006 Meetings Paper, Boston.

Chen, N. F., Roll, R., & Ross, S. A. (1986). Economic forces and the stock market. *Journal of Business*, 383-403.

Cheng, P., Lin, Z. L., & Liu, Y. (2011). Heterogeneous information and appraisal bias. In 46th *Annual AREUEA Conference Papers*.

Domowitz, I., Glen, J., and Madhavan, A. (1997). Market segmentation and stock prices: Evidence from an emerging market. *The Journal of Finance*, 52(3), 1059-1085.

Fairbairn, M. (2014). 'Like gold with yield': Evolving intersections between farmland and finance. *Journal of Peasant Studies*, 41(5), 777-795.

Ferson, W. E. (1990). Are the latent variables in time-varying expected returns compensation for consumption risk? *The Journal of Finance*, 45(2), 397-429.

Ferson, W. E., and Harvey, C. R. (1994). Sources of risk and expected returns in global equity markets. *Journal of Banking & Finance*, *18*(4), 775-803.

Fu, Chung-Hong. (2013). Timberland and farmland investments: separating the bark from the chaff. *Economic Research and Analysis*.

Geltner, D. (1993). Temporal aggregation in real estate return indices. *Real Estate Economics*, 21(2), 141-166.

Getmansky, M., Lo, A.W., and Makarov, I. (2004). An econometric model of serial correlation and illiquidity in hedge fund returns. *Journal of Financial Economics*, 74(3), 529-609.

Gibbons, M. R., & Ferson, W. (1985). Testing asset pricing models with changing expectations and an unobservable market portfolio. *Journal of Financial Economics*, 14(2), 217-236.

Hansen, L.P. (1982). Large sample properties of generalized method of moments estimators. *Econometrica, 50(4)*, 1029-1054.

Hanson, S. D., & Myers, R. J. (1995). Testing for a time-varying risk premium in the returns to US farmland. *Journal of Empirical Finance*, 2(3), 265-276.

Hardin, W., & Cheng, P. (2005). Farmland in a mixed-asset portfolio: A mean-semivariance approach. *Journal of Real Estate Portfolio Management*, 11(2), 187-195.

Harvey, C.R., Liu, Y., and Zhu, H. (2016). … and the cross-section of expected returns. *The Review of Financial Studies*, 29(1), 5-68.

Irwin, S.H., Forster, D.L., and Sherrick, B.J. (1988). Returns to farm real estate revisited. *American Journal of Agricultural Economics*, 70(3), 580-587.

Jorion, P., & Schwartz, E. (1986). Integration vs. segmentation in the Canadian stock market. *The Journal of Finance*, 41(3), 603-614.

Lee, M. L., Lee, M. T., & Chiang, K. C. (2008). Real estate risk exposure of equity real estate investment trusts. *The Journal of Real Estate Finance and Economics*, 36(2), 165.

Lewellen, J. (2011). Institutional investors and the limits of arbitrage. *Journal of Financial Economics*, 102(1), 62-80.

Lewellen, J., & Nagel, S. (2006). The conditional CAPM does not explain asset-pricing anomalies. *Journal of Financial Economics*, 82(2), 289-314.

Liu, C. H., Hartzell, D.J., Greig, W., and Grissom, T.V. (1990). The integration of the real estate market and the stock market: Some preliminary evidence. *The Journal of Real Estate Finance and Economics*, 3(3), 261-282.

MacKinlay, A.C. (1995). Multifactor models do not explain deviations from the CAPM. *Journal of Financial Economics*, 38(1), 3-28.

Mei, J., & Lee, A. (1994). Is there a real estate factor premium? *The Journal of Real Estate Finance and Economics*, 9(2), 113-126.

Pukthuanthong, K., Roll, R., and Subrahmanyam, A. (2019). A protocol for factor identification. *The Review of Financial Studies*, 32(4), 1573-1607.

Shiha, A. N., and Chavas, J.P. (1995). Capital market segmentation and US farm real estate pricing. *American Journal of Agricultural Economics*, 77(2), 397-407.

Shleifer, A., & Vishny, R. W. (1997). The limits of arbitrage. *The Journal of Finance*, 52(1), 35 55.

Stehle, R. (1977). An empirical test of the alternative hypotheses of national and international pricing of risky assets. *The Journal of Finance*, 32(2), 493-502.

Taylor, M. P., and Tonks, I. (1989). The internationalisation of stock markets and the abolition of UK exchange control. *The Review of Economics and Statistics*, 332-336.

Whyte, A. (2018). The biggest investors in real estate. *Institutional Investor*.

Zhang, L. (2005). The value premium. *The Journal of Finance*, 60(1), 67-103.

CHAPTER 4. OPTIMAL MIX OF RENTED AND OWNED FARMLAND INVESTMENT

Abstract

I develop a decision rule that guides farmers and agricultural investors in determining the optimal mix of owned and rented farmland based on operating income and capital gains. I do so by utilizing the minimum-variance portfolio approach with two risky assets, owned land and rented land. Applying this approach to farmland in West Central Indiana, my findings show the extreme favorability of owning rather than renting farmland.

Key terms: farmland, capital gain, minimum-variance portfolio, operating income

4.1 Introduction

What is the optimal mix of owned and rented farmland for a farm operator in a world in which operating income and capital gains are uncertain? This question has vexed farmland investors, particularly farm operators. It is a matter of either renting more land and increasing farm size and getting more operating income or owning more land (which may reduce farm size) and getting more capital gain. This decision is vital for managing risk of the farming business. Failure to address this question can have detrimental effects on a farm's financial performance.

When an investor, such a farm operator, buys an asset, he/she is entitled to reap the income provided by this asset over the ownership period in addition to the benefits (or gains) of selling it in a future point in time. When renting an asset, he/she acquires the income provided by the asset for the leasing period only (Smith and Wakeman, 1985). In other words, deciding whether to buy or lease farmland depends on their relative advantage. Since the early 1970s, there has been a considerable body of finance literature that has examined the buy/lease decision as mutually exclusive choices in the sense that it is a problem of either buying or leasing a capital asset. Within an agricultural context, the most dominant capital asset is farmland. In the U.S., for instance, farmland represents more than 80% of farm sector assets (Burns el al., 2018). Many academic (Boumtje et al., 2001) and practical (Agfax, 2018; Roddy, 2018) attempts have been developed to assist farmers and/or agricultural investors with the buy vs. lease decision. However, to the best of my knowledge, very few attempts have been made to help guide them in making a decision regarding partial ownership of farmland (i.e., mixed-tenure).

Over the span of the last several years, there has been an increase in mixed-tenure or partial ownership of farmland, especially for medium and large farm sizes (Bigelow et al., 2016). At the aggregate level, operators rent (own) around 45% (55%) of U.S. farmland. At the farm level, a typical full-time farmer rents 65% of the farmland he/she operates (Kirwan, 2009). So, mixed-tenure has become the norm. Earlier studies referred to the beginning of this trend since the early 1940s. For instance, Apland et al. (1984) showed that over the 1940 to 1978 period the percentage of U.S. farmland that is partially owned increased from 29% to 55%. Of course, there was a parallel decline in fully owned and fully rented farmland. This increase in partial ownership, coupled with the lack of studies regarding farmland buying and leasing decisions, points to the need for deeper theoretical and empirical investigation of the factors contributing to partial ownership. This chapter provides a theoretical contribution to the mixed-tenure decision.

My approach relies primarily on the distinction of operating income from capital gains on farmland. According to the discounted net present value model, given a constant discount rate, there should be a correspondence between farmland value and farmland income. However, most empirical findings do not support a correlated movement of farmland price and income. There exists a considerable body of literature showing a consistent divergence of farmland price from the discounted present value model of asset pricing. Some notable studies include Klinefelter (1973); Burt (1986); Featherstone & Baker (1987); Falk (1991); and Clark et al. (1993)).[5] This divergence is common across different geographic regions. According to these studies, expected income on farmland is not the main driver of changes in its price. Specifically, operating income and capital gains have different time series. Figure 1 demonstrates the operating income and capital gain for U.S farm real estate for the 2000 to 2018 period. For this 19-year period, the correlation between operating income and capital gains was around 0.58. This figure can be seen as the centerpiece of this study. I aim to use this finding to derive a decision rule of the optimal amount of farmland to buy and/or rent. So, my research question is as follows: *How are the moments of operating income and capital gain related to mixed-tenure farmland ownership?* This question may be asked in a different way. *Taking into account risk and expected return of owned land and rented land, what is the optimal mixture of operating income and capital gain for a farm to minimize risk?*

[5] Using Iowa farmland data over the period 1921 – 1986, Falk (1991) found that even though farmland price and rent are highly correlated, the causal relation between rent and price was not supported.

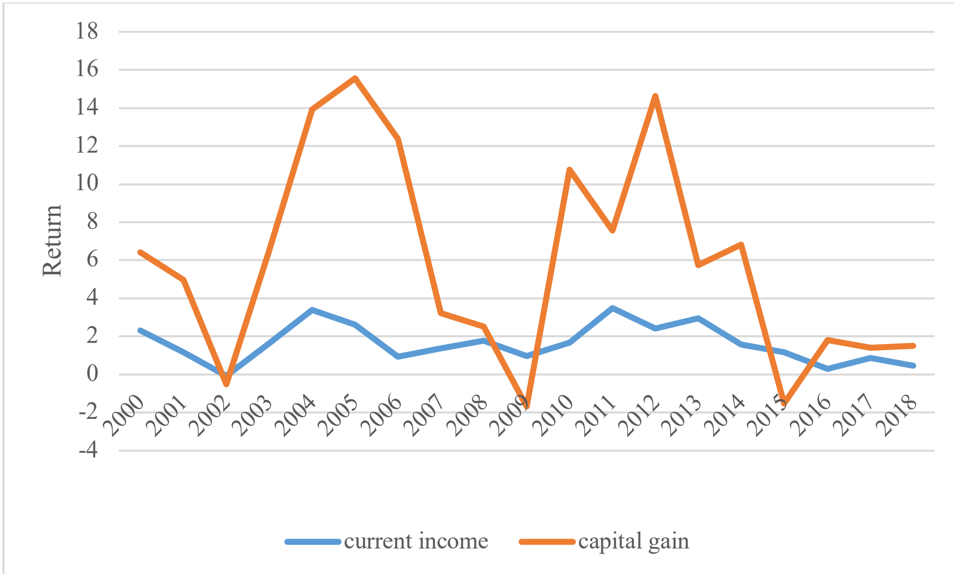

Figure 4.1: Capital Gain and Operating Income for the U.S. Farming Sector

I aim to model how farmland operating income, capital gain, and risk of one or both of these items are linked to the owned/rented farmland mixture decision. Since total return can be decomposed into operating income and capital gain, I can map rented/owned farmland to operating income/capital gain. If the majority of operated farmland is owned by the operator, then the majority of the return will be capital gain. On the other hand, if the majority of operated farmland is rented, then the majority of the return will be operating income.

Toward this aim, my approach is based on examining the mixture of rented and owned land as a portfolio of operating income and capital gain. I argue that adopting a portfolio perspective to find an optimal portfolio of operating income and capital gain can be mapped into the optimal mixture of owned and rented farmland. This is accomplished by considering a portfolio problem with two assets. The first asset is the wholly rented farmland in which all of the return is the operating income. The second asset is wholly owned farmland for which total return is comprised of operating income and capital gain.

My work contributes to the literature in several important ways. The foremost contribution is uniquely applying the portfolio approach to the buy vs. lease capital investment decision. To the best of my knowledge, I'm the first to test the presence of diversification benefit of a portfolio of operating income and capital gain. My work will also contribute to the farmland ownership literature. But unlike most of studies that empirically examine the economic impact of changing farmland ownership profile, I model how risk could affect the ownership structure of farmland. That is, I endogenize the ownership structure and exogenize the risk of both operating income and capital gain.

The rest of this chapter is organized as follows. In section 4.2, I shed light on the relationship between asset prices and earnings. Uncertainty of agricultural returns is uncovered in section 4.3. Section 4.4 describes the buying and leasing decisions of capital assets. I develop the conceptual framework in section 4.5. Numerical example with farmland returns data for West Central Indiana is shown in section 4.6. Conclusions and future research suggestions are discussed in section 4.7.

4.2 Prices and Earnings

In this section, I shed light on the relationship between asset price and the dividends or earnings from utilizing the asset. According to the efficient market hypothesis introduced by Eugene Fama in his PhD dissertation in 1964, market efficiency means that prices reflect all available information. The simplest form of market efficiency is that the asset price incorporates the expectation of future payout of dividends or earnings discounted at a constant discount rate. Formally,

$$P_t = E_t \sum_{k=0}^{\infty} \frac{D_{t+k}}{(1+r)^{k+1}} \tag{1}$$

where P_t is the price of capital asset at time t, D_t is the dividend or earnings at time t, r is the discount rate or the expected return, and E_t is the expectation operator based on information available at time t. In Eq (1), a constant dividend is assumed (i.e., dividends are not growing over time). If we incorporated the dividend growth rate (g) in the pricing of an asset, eq (1) becomes:

$$P_t = \frac{D_{t+1}}{1+r}\left(1 + \frac{1+g}{1+r} + \frac{(1+g)^2}{(1+r)^2} + \cdots\right)$$

And this corresponds to

$$P_t = \frac{D_{t+1}}{r-g} \tag{2}$$

Accordingly,

$$\frac{P_t}{D_{t+1}} = \frac{1}{r-g} \tag{3}$$

So, according to this model, if r and g are time invariant, the price-dividend ratio should be constant. Stated differently, if the discount rate and dividend growth rates are constant over time, the time series of prices and dividends should be parallel to each other or the price-dividend ratio should be constant. However, there is ample empirical evidence that the price-dividend ratio is variant over time. This is evident for most markets including the stock market, the real estate market, and the farmland market. For example, Shiller (2015) illustrates that the time series of real prices and earnings of the S&P composite index over the 1870 to 2014 is time variant (figure

2). In figure 3, Burns et al. (2018) presents the time series of farmland prices and farm income per acre over the period 1980-2016. They also showed that changes in cash rent lag behind changes in farmland values. That is an appreciation in farmland values is followed by a lower increase in cash rent and a decrease in farmland values is followed by a slower decrease in cash rent. Generally speaking, cash rent is stickier than farmland values.

This variation in the price dividend ratio (or price-earnings ratio) is explained by two opposing school of thoughts. Efficient market advocates argue that this is due to variation in expected return (or discount rate). The behavioral finance advocates argue that this is because the asset markets are not efficient. Whether the explanation is the efficient market theory or the behavioral finance, I take this variation as given and build on it by utilizing a model that computes the optimal mix of owned and rented farmland.

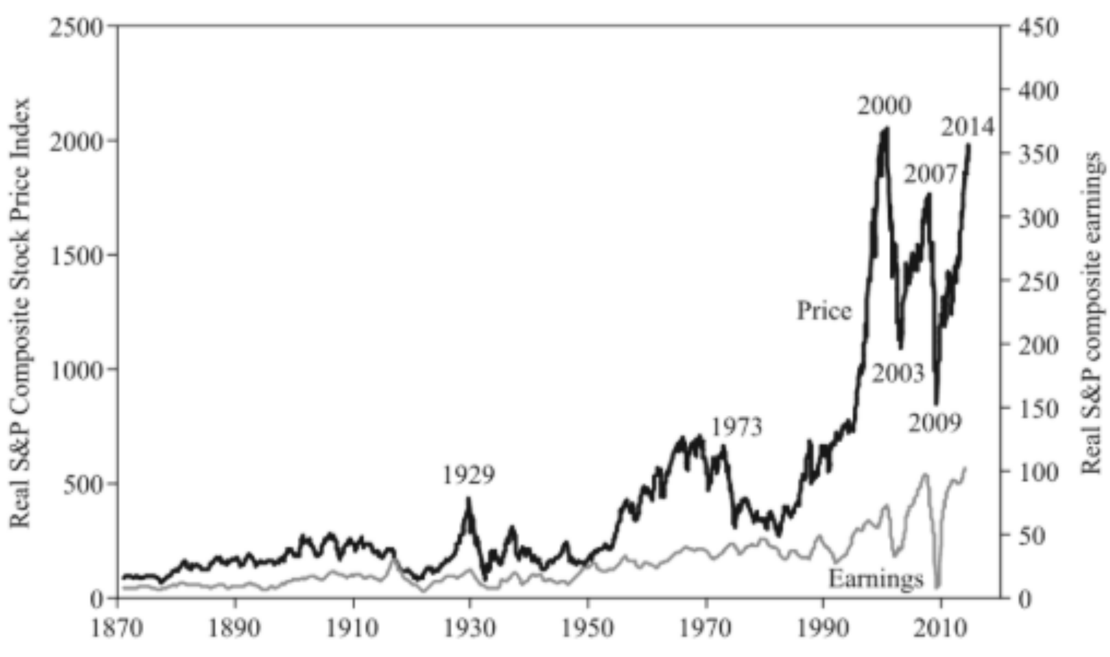

Figure 4.2: Real S&P Composite Index Price and Earnings, 1870-2014.
Source: Shiller (2015)

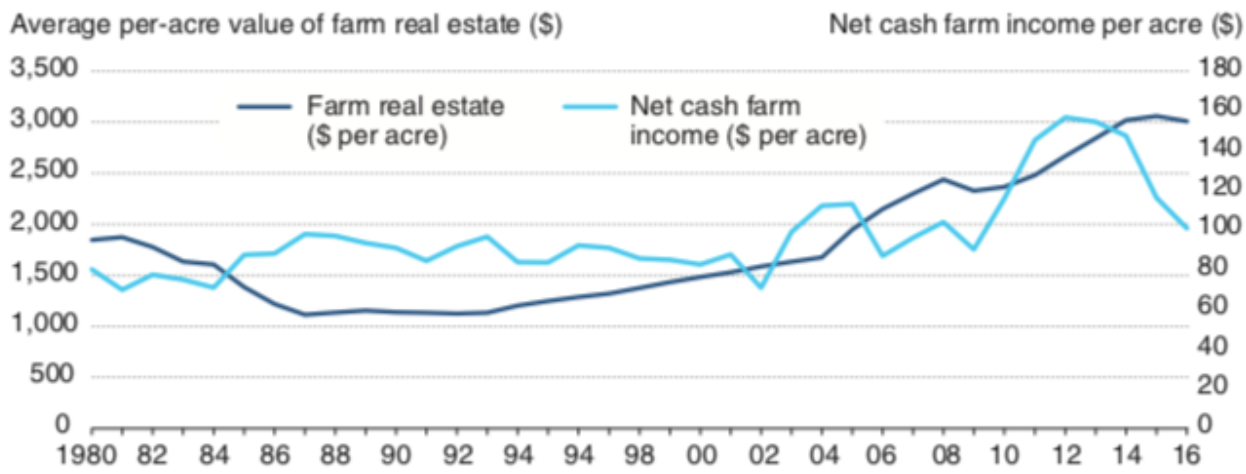

Figure 4.3: U.S. Farm Real Estate Value and Net Cash Farm Income per Acre, 1980-2016. Source: Burns et al. (2018)

4.3 Uncertainty of Agricultural Returns

One of the defining aspects of agricultural decision-making is uncertainty. Almost every farm operator and landowner make decisions characterized by risky outcomes (e.g., production and investment decisions). This is intensely reflected in academic work in the field of Agricultural Economics.[6] My research fits into this large strand of literature by focusing on how uncertainty of operating income and capital gains affect land tenure.

Based on the net present value model, the price of the farmland is the expected value of discounted future cash flows. However, most empirical studies failed to show the causal relationship between operating income and farmland value. There are even periods where lower operating income was associated with high farmland value. For instance, in the 1973 to 1980 period there was a consistent decline in net farm income and a consistent increase in farmland values (Shalit and Schmitz, 1982). I build on this finding by approaching the mixed–tenure

[6] A search for the word "uncertainty" in the American Journal of Agricultural Economics' website generates several dozen results.

farmland decision as a portfolio of operating income and capital gains, where both of them are uncertain.

Capital gains are of central importance to any farmland investor, including farm operators. Over time, capital gains have represented a large share of farm income. For example, Hoover (1962) showed that capital gains represented about 18% of net farm wealth over the 1940 to 1959 period. Over the 1952 to 1972 period, Melichar (1979) found that capital gains represented approximately 33% of net farm wealth. Recently, Langemeier (2017) showed that capital gains represent approximately 64% of the return on farm assets. This underscores the need to study the economic impacts of capital gains. Some studies have examined the economic consequences of capital gain uncertainty. For instance, using a real options framework, Turvey (2003) and Li (2016) showed that capital gain uncertainty is a crucial component of farmland value and that it is the main source of the wedge between the fundamental value of farmland and its actual price. I extend this strand of literature by studying the impact of operating income and capital gain uncertainty on farmland tenure structure.

4.4 Buy and Lease Decisions

Buying and renting any capital asset (e.g., farmland) are two critically important decisions for investors. Each one of them has its pros and cons. Renting the asset is better for liquidity management, since more working capital will be available for running the business. On the other hand, owning the asset allows you to gain an additional source of income, which is the appreciation in the asset value. Most studies pertaining to the buy/lease decision focus on determining which option is preferred to the other without considering the possibility of having a mixed strategy (owning part of total assets and renting the other portion).

Since the 1960s, several attempts have been made to model the buy/lease decision rule. The basic theme of this literature is selecting between renting and buying according to the net present value (NPV) rule. Buying (renting) is preferred to renting (buying) when it has a higher NPV than renting (buying). Examples are discussed in Johnson and Lewellen (1972), Gordon (1972), Schall (1974), among others. Other studies have focused on the identification of the determinants of the leasing or buying decision (Beatty et al., 2010; Eisfeldt and Rampini, 2009). Many determinants are mentioned in this literature including tax rates, capital market inefficiency, and liquidity.

My approach differs from the previously mentioned studies in two ways. First, unlike previous studies that looked at buying and leasing decisions as mutually exclusive, I pave the path for examining the possibility of renting some and buying the remainder of the assets used. My approach is particularly suitable for studying real estate in general and farmland in particular, where mixed tenure is widely seen. Second, previous models treat the asset as exogenous in the sense that the asset amount is determined before making the buy/lease decision. In contrast, my approach examines the asset value as endogenous and operating income, capital gains, and wealth as exogenous variables. I believe that by exogenizing wealth and endogenizing asset values, allows us to examine more interesting real-world cases.

4.5 Conceptual Framework

My argument is that the optimal mixture of owned and rented land can be conceptualized as a portfolio problem with two risky assets. The first asset is the wholly rented land with a return consisting entirely of operating income (net return from producing crops). The second asset is wholly owned land where the return is a portfolio of operating income and capital gains (farmland appreciation). Therefore, operating income is common to both assets, while capital gains are only included as part of the return on owned land. Intuitively, all else equal, when the operating income is greater than capital gains, the weight for rented land should be greater than the weight for wholly owned land. The underlying intuition, as I argued before, is that with a given investment, the operator's goal is to find the optimal mixture of owned and rented land.

A. *First Asset: Wholly Rented Farmland (Y):*

The first asset is the wholly Rented farmland whose return comes solely from operating income with a mean R_O and variance σ_O^2. R_O comes from the production of crops. So, in my model,

$$R_Y = R_O \tag{4}$$

According to (1), the only source of return for the asset (Y) is the operating income.

B. Second Asset: Wholly Owned Farmland (X):

The second asset is wholly owned farmland, which is seen as a portfolio of operating income and capital gains. Its return is the weighted average of the return on operating income and capital gains. Mathematically, the return on second asset X is as follows:

$$R_X = \alpha R_C + (1 - \alpha) R_O \tag{5}$$

where R_X is the return of the second asset X. R_C and R_O are the capital gain and operating income, respectively. Eq (4) is a weighted average of capital gain and operating income rather than their sum. The intuition for this is that our approach of optimizing the mix of owned and rented land is basically a mix of capital gain and operating income.

The variance of the wholly owned farmland X, $\sigma_{X,}$ is

$$\sigma_X^2 = \alpha^2 \sigma_C^2 + (1-\alpha)^2 \sigma_O^2 + 2\,\alpha\,(1-\alpha)\,\sigma_{C,O} \qquad (6)$$

where σ_C^2 and σ_O^2 are the variances of capital gains and operating income, respectively, and $\sigma_{C,O}$ is the covariance between capital gains and operating income.

Minimum variance portfolio problem can be used to minimize the variance of a portfolio composed of wholly rented land *X* and wholly owned land *Y*, irrespective of the required rate of return. The typical minimum variance optimization problem is:

$$\min_X \boldsymbol{W}^{`}\,\Omega\,\boldsymbol{W}$$

$$S.T\ \ \boldsymbol{W} \geq 0$$

where $\boldsymbol{W}$ is the vector of asset weights in the portfolio. In my model, the vector $\boldsymbol{W}$ is composed of ω_X and ω_Y for the weights of asset X and asset Y, respectively, and Ω is the covariance matrix.

Using typical mean-variance assumptions,[7] I solve for the weights in the minimum variance portfolio of ω_X and ω_Y, then, the proportion of wealth devoted to asset X. ω_X will be

$$\omega_X = \frac{\sigma_Y^2 - \sigma_{XY}}{\sigma_X^2 - 2\,\sigma_{XY} + \sigma_Y^2} \qquad (7)$$

According to Eq (7) the optimal weight of the wholly owned farmland (X) in the minimum variance portfolio is a function of the variance of return on wholly rented farmland (Y), σ_Y^2, the variance of wholly owned farmland (X), σ_X^2, and the covariance of X and Y, σ_{XY}.

I use a numerical example to compute the optimal mix of owned and rented farmland based on the Eq (7). In the process, I aim to derive a decision rule that helps agricultural investors and/or

[7] These assumptions are 1) investors are risk averse, 2) the problem is a single period, 3) there are no taxes and no transaction costs, and 4) there is no restrictions on borrowing and/or short selling.

farmers in making the mixed-tenure farmland decision. This rule is based on the volatilities and covariances of wholly owned farmland and wholly rented farmland.

The model parameters are estimated using annual data for west central Indiana. In particular, I relied on land values, cash rent, and net return to land in west central Indiana for the period 1960-2019. For this 60-year period, I estimate the returns on wholly owned farmland, returns on wholly rented farmland, variances of wholly owned and wholly rented farmland, and the covariances between them. For the return on wholly owned farmland, I use the following equation

$$Return_{X,t} = \frac{P_t - P_{t-1} + NI_t}{P_{t-1}} \qquad (8)$$

where P_t is the value of farmland at year t, and NI_t is operating income for farmland at time t. The return for the wholly rented farmland is

$$Return_{Y,t} = \frac{NI_t}{CR_t} \qquad (9)$$

Where NI_t is the net operating income from the production of crops at time t. According to Eq (9), the operator rents farmland for the amount CR_t in return for net operating income, NI_t. So, the problem is how much weight to devote to $Return_X$ and $Return_Y$ to minimize overall risk.

4.6 Numerical Example

Figure 4.4 shows the time series of owned farmland return and rented farmland return for west central Indiana. This figures essentially presents the time series expressed in Eq (8) and Eq (9). Note the difference between figure 4.4 and figure 4.1. Even though the capital gain is the dominant portion of owned farmland and the operating income is the sole return of rented farmland, the capital gain is more volatile than the current return in figure 4.1, whereas in figure 4.4 the return on rented farmland is more volatile than the return on owned farmland. This is primarily due to my approach of calculating owned farmland return and rented farmland return. The current income return in figure 4.1 is calculated by dividing the operating income by the value of farmland. However, the rented land return is calculated, as in Eq (9), by dividing operating income by cash rent.

Figure 4.4: Return on Owned and Rented Farmland 1961-2019, West Central Indiana

Note that the weights obtained from Eq (7) are weights of wealth allocated to owned and rented farmland. In order to convert these weights into weights of owned and rented farmland operated by an operator, we need to divide the allocated dollar amount by the price per acre.

Based on data on land values, cash rents, and net operating income in west central Indiana, cash rented land is far riskier than the owned land. Over the period of 59 years, 1961–2019, rented farmland had negative return for 36 years, while owned farmland had negative return for only 10 years. Table 4.1 shows the values of the estimated parameters required to estimate the weights for the owned and rented farmland in the minimum-variance portfolio.

Table 4.1: Estimated Parameters of the Minimum-Variance portfolio (1961-2019)

	Mean return	**Variance**	**Covariance with Owned land**
Owned Land	0.117	0.018	1.000
Rented land	-0.026	0.123	0.029

Applying Eq (7) and using the estimated variances and covariance of owned and rented farmland, I obtain a weight for owned farmland of 1.12, and a weight for rented farmland of a negative 0.12. The positive weight for owned farmland versus the negative weight for rented land indicates the attractiveness of owning farmland relative to renting farmland. Also, the negative value for the weight of rented land has an economic interpretation based on the assumptions of portfolio theory. It is interpreted as short selling in the stock market. That is, the investor borrows money at the risk-free rate and buys farmland that were previously rented. Note that the income data are reported by farmers and they are likely to underreport their farm income mainly for tax reasons. As found by Key (2019), farmers tend to report less farm income when they have more off-farm income. In other words, ceteris paribus, higher non-farm income implies higher marginal tax rate which encourage underreporting of farm income. Of course, this leads to underestimation of the total return.

4.7 Conclusions

The primary contribution of this chapter is the development of a simple approach to deciding how much of farmland operated should be rented and how much should be owned. I relied on portfolio theory to obtain the optimal mix of owned and rented farmland. I formulated the problem as a portfolio selection model with two risky assets. The first asset is owned farmland whose return consists of operating income and capital gains. The second asset is rented farmland, for which operating income is the only source of net returns. Applying this model to farmland in West Central Indiana yielded results that are in favor of owning, rather than renting, farmland. Put differently, owned farmland is strictly preferred to rented farmland in terms of risk and return.

It should be noted that this study is not a description of the real world. It can, however, be used as a guide. If data is not consistent with the weights of owned and rented farmland, this model helps guide us to the assumptions that may need relaxing. In other words, this model might be used as a baseline model. After the baseline case we may consider, for example, tax effects and credit constraints. In other words, future attempts might 1) incorporate the tax treatment of operating income and capital gains and 2) investigate how credit constraints affect the solution to the proposed model.

Regarding tax effects, interestingly, Williamson and Bawa (2018) reported that farmers and ranchers pay the top capital gain tax rate of 20%. In the same report, 40% of family farms reported that they realized some capital gains or losses during a year compared to 14% for the average individual taxpayer. Significant capital gain taxes are believed to affect the optimal mix of rented and owned farmland. So, relaxing the “no tax assumption” will lower the weight allocated to owned farmland.

With regard to capital market imperfections and resulting credit constraints, Weber and Key (2014) modelled credit constraints by assuming that the cost of buying land increases linearly with the debt-to-wealth ratio. With this approach, it is assumed that there is a certain positive factor by which the cost of borrowing increases with the debt-to-wealth ratio. Of course, credit constraints also have a negative effect on the weights allocated to owned farmland.

Moreover, in the previous analysis, I assumed constant returns to scale. That is, small farms have the same operating income per acre as large farms. In the case of increasing returns to scale, there will be more weight on rented land relative to owned land since renting is more common as farm size increases. Future research can extend this work by relaxing these assumptions.

4.8 References

Agfax, 2018. Des Keller: Farmland values: buy or rent to expand? It's a complicated choice. [Web page]. Retrieved from https://agfax.com/2018/01/08/farmland-values-buy-or-rent to-expand-its-a-complicated-choice/

Apland, J., Barnes, R. N., & Justus, F. (1984). The farm lease: an analysis of owner-tenant and landlord preferences under risk. American Journal of Agricultural Economics, 66(3), 376-384.

Beatty, A., Liao, S., & Weber, J. (2010). Financial reporting quality, private information, monitoring, and the lease-versus-buy decision. *The Accounting Review*, 85(4), 1215-1238.

Bigelow, D., A. Borchers, & Hubbs, T. 2016. U.S. farmland ownership, tenure, and transfer. EIB-161, USDA-ERS.

Boumtje, P.I., Barry, P.J., & Ellinger, P.N. (2001). Farmland lease decisions in a life cycle model. *Agricultural Finance Review*, Vol. 61 Issue: 2, pp.167-179, https://doi.org/10.1108/00214810180001122.

Burns, C., Key, N., Tulman, S., Borchers, A., & Weber, J. (2018). Farmland values, land ownership, and returns to farmland, 2000-2016. ERR-245, USDA-ERS.

Burt, 0. 1986. Econometric modeling of the capitalization formula for farmland prices, *American Journal of Agricultural Economics*, 68:10-26.

Clark, J.S., Fulton, M., & Scott, J.T. (1993). The inconsistency of land values, land rents, and capitalization formulas. *American Journal of Agricultural Economics*, 75(1):147–155.

Eisfeldt, A.L. & Rampini, A.A. (2009). Leasing, ability to repossess, and debt capacity. *The Review of Financial Studies*, 22(4), 1621-1657.

Falk, B. (1991). Formally testing the present value model of farmland prices. *American Journal of Agricultural Economics*, 73(1), 1-10.

Fama, E. F. (1960). Efficient market hypothesis (Doctoral dissertation, Ph. D. dissertation, University of Chicago, Graduate School of Business).

Featherstone, A.M. & Baker, T.G. (1987). An examination of farm sector real asset dynamics: 1910-85." *American Journal of Agricultural Economics* 69(3): 532-46.

Gordon, M.J. (1974). A general solution to the buy or lease decision: A pedagogical note. *The Journal of Finance*, 29(1), 245-250.

Hoover, D.M. (1962). The measurement and importance of real capital gains in United States agriculture, 1940 through 1959. *Journal of Farm Economics*, 44(4), 929-940.

Johnson, R.W. & Lewellen, W.G. (1972). Analysis of the lease-or-buy decision. *The Journal of Finance*, 27(4), 815-823.

Kirwan, B. 2009. The incidence of U.S. agricultural subsidies on farmland rental rates. *Journal of Political Economy,* 117(1): 138–64

Klinefelter, D. A. (1973). Factors affecting farmland values in Illinois. *Illinois Agricultural Economics, 27-33.*

Langemeier, M. (2017). US farm sector financial performance. *farmdoc daily*, 7.

Li, X. (2016). The farmland valuation revisited. *International Journal of Food and Agricultural Economics (IJFAEC)*, 4(1128-2016-91987), 11.

Melichar, E. (1979). Capital gains versus current income in the farming sector. *American Journal of Agricultural Economics*, 61(5), 1085-1092.

Roddy, D. (2018). Renting or buying farmland: which is right for you. [Web page]. Retrieved from https://emergence.fbn.com/buying-vs-renting-farmland-pros-cons.

Schall, L.D. (1974). The lease-or-buy and asset acquisition decisions. *The Journal of Finance*, 29(4), 1203-1214.

Shalit, H. & Schmitz, A. (1982). Farmland accumulation and prices. *American Journal of Agricultural Economics*, 64(4), 710-719.

Shiller, R. J. (2015). Irrational exuberance: revised and expanded third edition. New York: Princeton University Press.

Smith, C.W. & Wakeman, L.M. (1985). Determinants of corporate leasing policy. *Journal of Finance* 40, 895-908.

Turvey, C. (2003). Hysteresis and the value of farmland: A real-options approach to farmland valuation. Government Policy and Farmland Markets: The Maintenance of Farmer Wealth, *Iowa State Press*, pages 179–207.

Weber, J. G. & Key, N. (2014). Do wealth gains from land appreciation cause farmers to expand acreage or buy land? *American Journal of Agricultural Economics*, 96(5), 1334-1348.

Williamson, J. M., & Bawa, S. G. (2018). Estimated effects of the tax cuts and jobs act on farms and farm households. ERR-252, USDA- Economic Research Service.

CHAPTER 5. OVERALL CONCLUSION

As a dominant agricultural asset coupled with its surge in values during the recent two decades, farmland has attracted a great deal of interest for investors. For instance, institutional investors have started to allocate some of their funds toward farmland investing. This dissertation shed light on farmland pricing and management. For pricing and valuation of farmland, I showed in chapter two that farmland, on average, has lower risk compared to the market portfolio. However, I also showed heterogeneity in reward to risk ratio of farmland locations and qualities. In particular, my results showed that i) Indiana farmland has more diversification benefits than Iowa farmland and ii) adding the quality dimension to the location dimensions improves diversification benefits for Indiana, but not for Iowa. The main contribution of this research is paving the path for diversification based on quality which is overlooked in prior research.

Also, within farmland pricing, chapter three answers a critical question whose answer points to a critical difference between real estate and farmland investments. Given that farmland and real estate are both real assets and they are both regarded as consumption and capital goods, I ask whether farmland, as real estate, has a common risk factor to which exposure has a risk premium. Using farmland NCREIF quarterly data for the period 1991-Q1 to 2016-Q2, my analysis shows that farmland has neither a statistical nor an economical common risk factor. Put differently, I could not find a risk-based explanation for the risk adjusted return on farmland. Other dimensions, like farmland illiquidity, or even the broad non-risk behavioral theories may play a role in describing the relatively high Sharpe ratio or risk adjusted return of U.S. farmland.

Looking at farmland management, in the fourth chapter, I focused on the buying/renting decision of farmland. Since most U.S. farmland are operated under mixed tenure arrangement where part of the operated farmland is owned while the remaining part is rented. In this chapter, I basically aimed to find the optimal mix of owned and rented farmland operated by an agricultural investor in light of uncertain capital gain and operating income. Therefore, I employed the mean-variance mathematics to find the optimal portfolio of owned and rented farmland. Applying this model to farmland in West Central Indiana, my findings showed the extreme favorability of owning rather than renting farmland.