Is Farmland a Common Risk Factor in Asset Pricing Models?

September 24, 2020

Job Market Paper

Ashraf Noumir (corresponding author)
Research Assistant
Department of Agricultural Economics
Purdue University
anoumir@purdue.edu

and

Michael Langemeier
Professor
Department of Agricultural Economics
Purdue University
mlangeme@purdue.edu

Is Farmland a Common Risk Factor in Asset Pricing Models?

Abstract

Farmland represents the largest 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 paper 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 exhibit diversification benefits, it fails to be a risk factor. Instead, market frictions and / or non-risk explanations might provide a more plausible description of farmland's high risk-adjusted return.

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

JEL codes : C58, G11, G12.

Introduction

The aim of this study, as described in its title, is to examine whether farmland exhibits a risk factor that is compensated with higher return. The primary motivation for this study is the well-documented presence of a real estate risk factor (Mei and Lee, 1994; Lee *et al*, 2008; Carmichael and Coën ,2018; among others) in addition to the similarities in investment performance between real estate and farmland such as 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). In particular, Given the similar investment characteristics of real estate and farmland, is there a farmland risk factor that affects and explains the cross section of stocks return? 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 provides support for the non-risk and / or market frictions explanation for farmland's high return (i.e., irrational investors, and transactions costs). Put differently, the relatively high 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 has become 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 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. In contrast, less than 500 institutional investors hold around 84% of all U.S. real estate investments (Whyte, 2018).

It is important for investors to answer the question: are there factors out there that drive asset returns? Pukthuanthong et al. (2018) pointed to two interesting empirical regularities that show that i) at least one risk factor exists that affect stock returns, and ii) the existence of multiple risk factors. The first point indicates that there is a lower bound to the volatility / risk of a well-diversified portfolio. This suggests that there is at least one risk factor affecting the return of portfolio constituents (i.e., however diversified the portfolio is, 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 is only one risk factor, 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 were assumed to 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 our analysis, we employ the time-varying expected return method for two reasons. First, if it does not help, it adds no harm. Second, as far as we 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 in 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, we used the latent multifactor asset pricing model. Conditional betas are estimated with the generalized method of moments (GMMs). Instruments needed for the latent multifactor asset pricing model are obtained from the Federal Reserve Bank of St. Louis (FRED) and Robert Shiller's website.

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. We use this "risk factor" approach to examine whether farmland has a role in explaining asset pricing. We present evidence that there is no farmland risk factor. Our 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" we 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 paper 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 our knowledge, we are the first to empirically examine a farmland risk factor and its effect on common stocks' returns. In addition, our findings add more insight to the reluctance of institutional investors to invest in farmland.

The rest of this paper is organized as follows. In section I, we discuss the related literature highlighting the exogenous and endogenous approaches to factor risk pricing. Section II describes the methodology and econometric model. Data description and sources are discussed in section III. Sections IV and V present the empirical results and conclusions, respectively.

I. Literature Review

This paper 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 an 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) in 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. We extend this line of literature by documenting whether this performance has a risk relationship to the U.S. stock market

We 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 obtain the risk premium, investors should incorporate 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) used the Fama-MacBeth cross-sectional, time series approach to test the integration vs. segmentation hypothesis. The low power of the Fama-MacBeth regression motivated Jorion and Schwartz (1986) to use the maximum likelihood approach since it has more power than the Fama-MacBeth 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. In other words, 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,[1] 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.

[1] 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.

Our work extends Carmichael and Coen's work by examining the presence of a farmland factor in predicting the cross-section of stock returns.

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, we fill this gap by examining the potential role of farmland in the cross-section of assets' returns. In doing so, we choose the exogenous approach to factor pricing.

II. Methodology

In this section we describe the latent variable asset pricing model and the econometric estimation of the model parameters.[2] 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

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

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

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

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

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

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

$F_{t+1} = \phi_0 + \phi_1\,Z_t + f_{t+1}$ (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:

$E_t\,(R_{t+1}^{I}) = \varphi_0 + \varphi_1\,Z_t$ (6)

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

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

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

$$F_{t+1} - \phi_0 - \phi_1 Z_t = f_{\ t+1} \qquad (8)$$

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

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

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^{II}_{t+1}) 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 any distributional assumption on the residuals. In other words, it allows for serial correlation and/or heteroskedasticity of the error term. Therefore, GMM is regarded as more general model than OLS and GLS. We are 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 we use Hansen's J_T statistic with the two-step GMM estimation.

III. Data

We proxy farmland return with the National Council of Real Estate Investment Fiduciaries (NCREIF) farmland property index. Specifically, we 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. 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.[3]

We 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 our 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

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

subtracted from each decile portfolio. We transferred these data from monthly to quarterly frequency to match the farmland NCREIF index.

We 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. We 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).

IV. Empirical Results

In this paper, we 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, we 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 1. Over the period 1991 – 2016, the farmland factor (measured by farmland NCREIF) has a higher average quarter return (3%) than the return of the value weighted market index MKT (2%), corresponding to an annual return of 12% for farmland and 8% for the market. 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 we 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.

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.

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 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, we 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 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. We 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 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. Our results confirm this 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. We 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.

To gauge the robustness of our results across different portfolios, we repeat our analysis using equal-weighted size portfolios. Within each size decile, an equal weighted portfolio is formed. Table 3 reports summary statistics and table 4 reports the estimation results for equal-weighted portfolios. Generally speaking, the results are quite similar to those in table 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-value of 0.5108, suggesting that we cannot reject the null hypothesis at the 5% level that the model is well specified.

Since F_NCREIF is an appraisal-based index, our estimates of average returns and volatility may suffer from appraisal bias. As we 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 our results, we desmoothed the F_NCREIF index using the following equation:

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

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 that M is approximately 0.40 for real estate assets. So, we also adopted this value for M. Table 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 1, descriptive statistics show that farmland has a superior Sharpe ratio relative to the market factor. However, the rest of our 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.

V. Conclusions

In this paper, we 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. These findings point to major difference between the risk behaviors of farmland and real estate. It is worth noting that our findings do not suggest that farmland is not an interesting asset class to institutional investors. Investors still could benefit from the abnormal return associated with farmland investment which is not explained by the asset pricing model. What we have shown in this paper 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 our framework. First, because the farmland NCREIF index started in the first quarter of 1991, the time period we 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. We 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 change hands in a given year (Burns et al., 2018).

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.

Table 1

Summary Statistics: Quarterly Data, 1991:1 - 2016:6

	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 and second order autocorrelation coefficients, ρ_1 and ρ_2, 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.

Table 2

The Two Factor ICAPM (1991:01 - 2016:06) - 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.

Table 3

Summary Statistics (Equal-Weighted Portfolios): Quarterly Data, 1991:1 - 2016:6

	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.

Table 4

The Two Factor ICAPM (1991:01 - 2016:06) - 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.

Table 5

The Two Factor ICAPM (1991:01 - 2016:06) - 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 we 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).