Farmland Investment Characteristics from a Forward-Looking Perspective: An Explanation for the "High Return/Low Risk" Paradox

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Farmland Investment Characteristics from a Forward-Looking Perspective: An Explanation for the "High Return/Low Risk" Paradox

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ABSTRACT *Land values and cash rents are slow to adjust, and therefore the returns from owning farmland may be time varying and serially correlated. This article investigates a farmland portfolio's nominal and real returns from a forward-looking perspective, taking into account time-varying return and serial correlation. The results indicate that the attractive average return level observed historically can be attained only over a long investment period. The risk involved in the long investment period, however, is also substantial. As a result, in mixed-asset investment portfolios, the allocations to farmland are much lower than traditional mean-variance optimization implies.* (JEL Q15)

1. Introduction

Farmland investment has been shown to exhibit large expected returns and low risk and to allow diversification benefits within portfolios. Kaplan (1985) showed that the farmland asset class had equity-like return, bond-like volatility, and a low return correlation with traditional asset classes. Barry (1980) found that farmland returns added mostly nonsystemic risk to a well-diversified portfolio of stocks and bonds. More recent studies, including those by Irwin, Forster, and Sherrick (1988), Hennings, Sherrick, and Barry (2005), Noland et al. (2011), Sherrick, Mallory, and Hopper (2013), and Baker, Boehlje, and Langemeier (2014), among others, found similar results in terms of the superior characteristics of farmland returns.

With changing economic conditions, expected farmland return will vary over time (Bjornson 1995). As a result, past performance will not be an indicator of future performance. One reason that previous studies on farmland portfolio performance do not completely account for time-varying expected returns is that they are typically performed under Markowitz's mean-variance (M-V) framework (Markowitz 1968). The M-V model requires the mean and variance-covariance of asset returns as model inputs and does not allow the expected return to vary over time. These inputs are typically obtained from historical sample statistics.

In addition to time-varying expected returns, Moss, Featherstone, and Baker (1987) provide evidence showing that, unlike stock asset returns, farmland asset returns are correlated over time. The authors also indicate that failing to account for this autocorrelation may result in inappropriate estimates of the variance-covariance of asset returns. Moss, Featherstone, and Baker's research accounts for autocorrelation and shows the implication of this autocorrelation on multiperiod investments. However, they assume constant expected return by imposing steady-state initial conditions on the asset return variables.

While time-varying and serially correlated prices have been studied in the housing market (Riddel 2001), this article is the first to account for autocorrelation and time-varying expected returns in a model of multivariate farmland returns. The model is used to make forward-looking estimations and predictions of farmland portfolio investment risk and return.

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Appendix materials are freely available at http://le.uwpress.org and via the links in the electronic version of this article.

Time-series techniques are used to model individual land return series. Spatial correlations (Zhang and Nickerson 2015) among multiple land return series are estimated using copulas. An advantage of the copula approach is that marginal distributions are not limited to normality and can thus be extended to allow for the potential fat-tailed returns that exist in farmland returns. Optimal forward-looking farmland-only investment portfolios, as well as mixed-asset portfolios incorporating traditional asset classes, are constructed. The forward-looking risk-return profile is then evaluated in comparison with the corresponding mean-variance optimization outcome using historical asset returns as model inputs. To rule out the possibility that results are driven by inflation, both nominal and real returns are considered.

The results suggest that the forward-looking farmland investment risk-return profile is significantly different from the risk and return observed historically. As of 2017, the expected return is low in the short term, and it then recovers over a longer period. It takes multiple years for the expected return to reach the long-term equilibrium. The forward-looking expected return varies across different holding periods, and the high average return relative to risk observed historically can be attained only through long-term investment. The results show that while superior return can be expected through long-term investment, the risk involved in the long holding period is also considerably higher than implied by simple historical sample volatility. The results hold in terms of both nominal and real farmland returns. This indicates that the M-V optimization outcome obtained from historical sample statistics can be misleading in describing the forward-looking farmland investment risk-return profile. Within a mixed-asset optimal portfolio context, farmland constitutes a minimal component, especially for long holding periods; whereas traditional M-V optimization implies a substantial allocation to farmland. These findings may help explain the "high return and low risk" puzzle in farmland investment and provide potential investors and policy makers with a better understanding of the characteristics of this nontraditional asset class.

Our results are based on annual state-level farmland returns, as well as annual returns for financial assets such as common stocks, treasury bonds, and corporate bonds. While farmland assets are typically held for a long time, financial assets are held for much shorter periods. Therefore, an annual representation of stock and bond index returns may understate the true risk that individual investors in these assets bear. In addition, taxation differences exist and typically favor holding real assets over financial assets. This may increase the proportion of real assets in investor's portfolios.

2. Empirical Framework

Capitalization Theory

Assuming a constant discount rate and expected growth rate, the relationship between cash rents and land values can be represented by the capitalization model (Featherstone, Taylor, Gibson 2017).

$$L_t = C_t \,/\, (r - g), \tag{1}$$

where L_t is the land value at time t, C_t the cash rent to land at time t, r is the discount rate, and g is the income growth rate. The holding period return from owning land can be calculated as

$$R_t = \frac{L_t - L_{t-1} + C_{t-1}}{L_{t-1}} = \frac{L_t}{L_{t-1}} - 1 + r - g. \tag{2}$$

The annual growth rate of farmland prices $(L_t \,/\, L_{t-1} - 1)$ is significantly autocorrelated (Lence 2014). Therefore, it is reasonable to assume that farmland returns, according to equation [2], are also correlated over time.[1] This assumption is consistent with the empirical observations provided by Moss, Featherstone, and Baker (1987). In this article, the autocorrelation in farmland return series is accounted for using time-series techniques.

[1] This simple illustration is a characterization, which should not be treated as exact. Realized returns are also affected by factors such as leverage, and correlations will not be constant over time.

Time-Series Models

Time-series models have long been used in describing economic and financial data (Cochrane 2005; Tsay 2005; Adhikari and Agrawal 2013). The autoregressive-moving-average (ARMA) process (Box et al. 2015) is particularly useful for modeling time-series data and for predicting future values based on past observations (McGough, Plantinga, and Provencher 2004). The ARMA model accounts for potential autocorrelation in the series and allows for time-varying expected values.

Defining the lag operator L as $Lx_t = x_{t-1}$, an ARMA(p, q) process can be written as

$$\left(1-\sum_{i=1}^{p}\varphi_i L^i\right)y_t = \left(1+\sum_{j=1}^{q}\theta_j L^j\right)\varepsilon_t, \quad [3]$$

or $\varphi(L)y_t = \theta(L)\varepsilon_t$, where $\varphi(\cdot)$ and $\theta(\cdot)$ are the pth and qth lag polynomials, respectively.

An appropriate ARMA model for a specific time-series dataset can be selected and estimated by Box-Jenkins methodology (Box et al. 2015). The methodology follows a three-step procedure: model identification, parameter estimation, and diagnostic checking. Specifically, the orders p and q of an ARMA(p, q) model are first tentatively selected. The parameters of the model are then estimated from the data. Finally, diagnostic tests are performed to check the adequacy of the estimated model in describing the data. This three-step procedure is iterated until the satisfactory model is identified.

Copulas

Correlations among multiple time series can be modeled by copulas. Copulas were introduced by Sklar (1959). According to Sklar's theorem, if F is an arbitrary k-dimensional joint continuous distribution function, there is a unique associated copula that is defined as a continuous function C: [0, 1]$k \rightarrow$ [0, 1], which satisfies the equation

$$F(x_1,\ldots,x_k) = C[F_1(x_1),\ldots,F_k(x_k)],\ x_1,\ldots,x_k \in R, \quad [4]$$

where $F_1(x_1),\ldots,F_k(x_k)$ are the respective marginal distributions.

In this way, the joint distribution of $x_1,\ldots,x_k$ can be described by the marginal distributions F_i, and the correlation structure captured by the copula C. Note that the copula function is flexible in the sense that the variables x_i can be modeled with any kind of marginal distributions. In turn, if the marginal distributions are continuous, a unique copula exists corresponding to the joint distribution. That is,

$$C(u_1,\ldots,u_k) = F[F_1^{-1}(u_1),\ldots,F_k^{-1}(u_k)], \quad u_1,\ldots,u_k \in [0,1], \quad [5]$$

where $F_1^{-1}(\cdot),\ldots,F_k^{-1}(\cdot)$ are the corresponding quantile functions. Therefore, the copula can be defined as an arbitrary multivariate distribution on [0, 1]k with all marginal distributions being uniform.[2]

Let c denote the density function of the copula, C, which can be described as

$$c(u_1,\ldots,u_k) = \left(\frac{\partial^k C(u_1,\ldots,u_k)}{\partial u_1 \cdots \partial u_k}\right), \quad [6]$$

and the corresponding joint density function of $x_1,\ldots,x_k$ can be written as

$$f(x_1,\ldots,x_k) = c[F_1(x_1),\ldots,F_k(x_k)]\prod_{i=1}^{k} f_i(x_i), \quad [7]$$

where $f_1(x_1),\ldots,f_k(x_k)$ are marginal density functions.

There are different basic parametric copula families. The most frequently used are elliptical copulas and Archimedean copulas (Power, Vedenov, and Hong 2009; Cooper et al. 2012). The standard Gaussian copula from the elliptical family is used in this article. The Gaussian copula takes the form of

$$C^N(u_1,\ldots,u_k \mid \Sigma) = \Phi_\Sigma[\Phi^{-1}(u_1),\ldots,\Phi^{-1}(u_1)], \quad [8]$$

where Φ_Σ is a k-dimensional normal distribution with zero mean and correlation matrix $\mathbf{\Sigma}$,

[2] It is acknowledged that there are limitations to this approach. Time-varying correlations across different asset types are not accounted for by the copula models used in this article. A reviewer pointed out that farmland typically benefits from a flight to quality, which can be driven by the scale of market movements. This feature can be captured by our copula approach.

and Φ^{-1} is the inverse distribution function of the standard normal distribution.

3. Empirical Application

Data and Methodology

Our dataset for the farmland-only portfolio consists of annual state-level nominal cash rents and land values for cropland in 15 major agriculture-producing states in the United States from 1967 to 2017. All the data are taken from the USDA National Agricultural Statistics Service (NASS) database.[3] The annual rate of return is calculated as the sum of cash rents and capital gain divided by land value.[4] Real returns are derived by adjusting nominal returns, using the corresponding consumer price index as a measure for inflation.

To account for potential autocorrelation and time-varying expected return, the individual return series in each of the 15 states is first modeled using the ARMA models. A Ljung-Box test (Ljung and Box 1978) is used to check if autocorrelation exists in the individual return series. The test results indicate that the null hypothesis is rejected for both the nominal and real farmland return series in all 15 states. This indicates that there are significant autocorrelations in the farmland return series.[5] The individual return series are fitted using four candidate models, namely, ARMA(1,1), AR(1), MA(1), and white noise models.[6] The Student's t distribution is used to account for potentially heavy tails. If the estimated degree of freedom of the Student's t error distribution is greater than 10, a normal distribution is used. The Bayesian information criterion is used to select the best model. Model sufficiency is tested by performing a one-sample Kolmogorov-Smirnov (K-S) goodness-of-fit test on the standardized residuals. The p-value from the K-S test is greater than 5% for all the return series. A Ljung-Box test is performed again on the residuals; this shows that there is no autocorrelation in the residual series. Appendix A presents an estimated time-series model for each of the return series. For all states included in this study, AR(1) is the most appropriate time-series model for both nominal and real farmland returns.

Table 1 shows the projected mean, standard deviation, and coefficient of variation (CV) of nominal farmland returns with different holding periods from the time-series model, as well as the historical sample mean, standard deviation, and CV for individual states. Due to recent poor performance, the one-year-out expected return is much lower than the historical average. When we extend the holding period, the expected return begins to recover. This recovery speed varies across different states. The expected return exceeds the historical level in a ten-year holding period for Louisiana. For other states, the expected return within ten years is lower than the historical average. The standard deviation of the returns generally falls with a longer holding period, but that is not always the case. Minnesota has a one-year standard deviation of 11.75% and a five-year deviation of 12.45%. A longer period entails larger uncertainty with the existence of autocorrelation; however, the diversification effect over time tends to reduce the total risk within the entire holding period. These two offsetting effects cause a somewhat ambiguous relationship between volatility and the length of the holding period. Appendix B shows the corresponding real-return statistics, and similar results are observed.

In order to construct the optimal portfolio, the correlation structure of the multivariate

[3] See https://www.nass.usda.gov/.

[4] Changes in the portion of rented farmland may impose bias on the cash rent data. However, as the landowners who rent out farmland account for the majority of all landowners in the United States (Zhang 2015), it seems unlikely that the potential bias can render the analysis in this article invalid.

[5] A reviewer pointed us to a large literature on commercial real estate smoothing bias. See, for example, Geltner, MacGregor, and Schwann (2003). This bias exists in real estate markets such as land because appraisers have limited information on factors that influence value. Instead, they weigh recent transactions and other information such as marketwide appraisals in a manner that smooths appraisals across time. This phenomenon may be partially responsible for the autocorrelation we detect.

[6] The unit root is checked for all the return series, using the augmented Dickey Fuller (ADF) test. The null hypothesis is rejected at the 5% significance level for 13 of the 15 nominal return series, and at the 10% significance level for all 15 nominal return series. The null hypothesis is rejected at the 5% significance level for all 15 real return series. Therefore, we assume no unit root for the return series.

Table 1

Statistics of Farmland Nominal Returns in Individual States

	Projected 1 Year			Projected 5 Year			Projected 10 Year			Historical		
	$E(r)$	$\sigma(r)$	CV	$E(r)$	$\sigma(r)$	CV	$E(r)$	$\sigma(r)$	CV	$E(r)$	$\sigma(r)$	CV
Arkansas	8.92%	7.30%	0.82	10.75%	6.17%	0.57	11.33%	5.09%	0.45	13.22%	8.94%	0.68
Illinois	5.79%	10.96%	1.89	10.34%	9.75%	0.94	11.83%	7.76%	0.66	13.58%	11.26%	0.83
Indiana	5.54%	10.49%	1.89	9.19%	11.10%	1.21	11.11%	10.22%	0.92	14.49%	11.71%	0.81
Iowa	5.00%	11.95%	2.39	9.89%	11.00%	1.11	12.04%	9.58%	0.80	16.01%	13.57%	0.85
Kansas	0.70%	8.86%	12.66	5.71%	8.56%	1.50	8.08%	7.31%	0.90	13.36%	10.48%	0.78
Louisiana	9.74%	7.85%	0.81	10.97%	7.09%	0.65	11.53%	6.08%	0.53	10.92%	9.23%	0.85
Michigan	4.64%	7.68%	1.66	8.14%	7.00%	0.86	9.70%	6.11%	0.63	12.56%	9.55%	0.76
Minnesota	5.35%	11.75%	2.20	9.04%	12.45%	1.38	11.06%	12.27%	1.11	16.66%	13.36%	0.80
Mississippi	8.08%	8.20%	1.01	9.96%	8.57%	0.86	11.03%	8.01%	0.73	13.88%	10.51%	0.76
Missouri	7.45%	10.08%	1.35	11.91%	8.36%	0.70	13.39%	6.76%	0.50	15.57%	10.68%	0.69
North Dakota	3.29%	9.17%	2.79	9.71%	8.36%	0.86	12.56%	7.18%	0.57	17.31%	12.36%	0.71
Ohio	5.82%	11.75%	2.02	9.66%	11.34%	1.17	10.99%	9.72%	0.88	13.19%	10.90%	0.83
South Dakota	6.95%	14.46%	2.08	13.71%	14.38%	1.05	15.95%	11.01%	0.69	19.34%	11.78%	0.61
Texas	7.40%	9.82%	1.33	9.75%	8.78%	0.90	10.64%	7.45%	0.70	10.88%	8.43%	0.77
Wisconsin	8.58%	8.07%	0.94	10.68%	8.39%	0.79	11.81%	7.83%	0.66	16.22%	11.85%	0.73

Note: CV, coefficient of variation.

time-series residuals is then estimated by the Gaussian copula using maximum likelihood.[7] With estimated copula models and marginal time series, an optimal investment portfolio is constructed by the following procedure:

1. A sample of the standardized residuals is simulated from the copula model.
2. Individual returns for future time periods are projected using the simulated residuals and the respective marginal time series.
3. The portfolio return is calculated as the weighted average of individual returns.
4. Portfolio weights are optimized by maximizing the portfolio return with a given risk level.

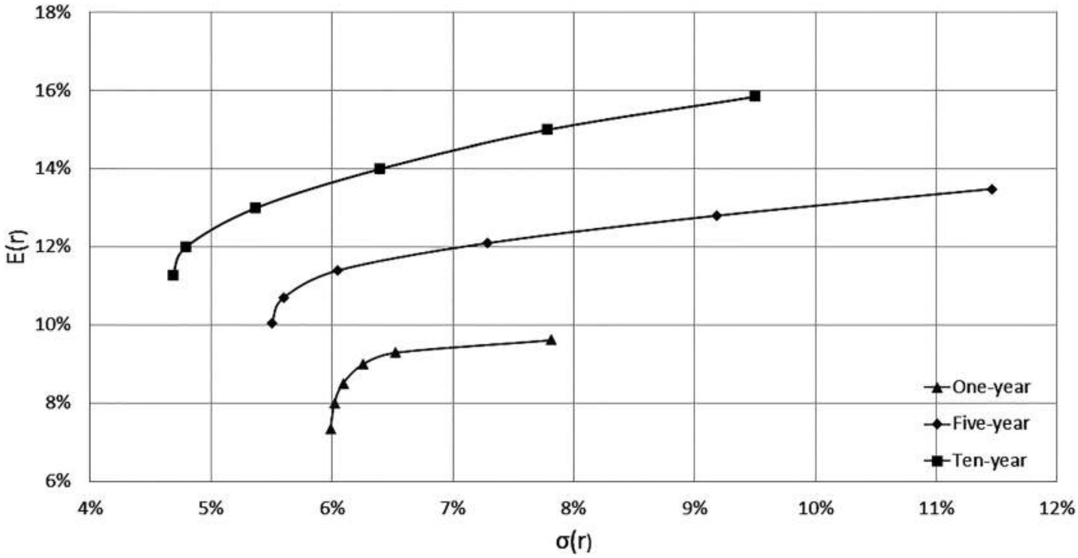
Using this ARMA-copula model, the optimal portfolio is constructed based on forward-looking return series instead of historical average return and sample volatility. Future expected return and risk are projected using time-series techniques for each return series. Correlation structure is retained by simulating time-series residuals from the estimated copula model. Optimal portfolio weights are calculated by maximizing future expected portfolio return at given risk levels. Appendix C and Appendix D show the forward-looking as well as M-V optimal portfolio weights using nominal and real returns, respectively.

For the mixed-asset portfolio analysis, our dataset consists of annual returns for four asset classes—farmland, common stocks, Treasury bonds, and corporate bonds—from 1976 to 2017. Following Hardin and Cheng (2002), an equally weighted index across all 15 states is used as a measure for farmland return. The S&P 500 index including dividends and before taxes is used as a measure for common stocks, the 10-year Constant Maturity Treasury is used for treasury bonds, and BBB- and AAA-rated bonds for corporate bonds. Again, a Ljung-Box test is performed to check if autocorrelation exists in these return series. The null hypothesis of no autocorrelation is rejected only for the farmland index returns. The test results hold for both nominal and real returns. The same methodology is used to estimate marginal time series and the correlation structure of residuals. Appendix E presents estimated time-series models for the four asset classes. While the AR(1) time-series model is used for farmland, the white noise model is selected for the other asset classes.[8]

[7] To account for any potential tail dependence, Student's *t* copula is also used as an alternative model to estimate the correlations. There is no significant impact on investment portfolio's risk-return profile.

[8] The stationarity (no unit root) of the return series is checked and confirmed using the augmented Dickey Fuller test.

Figure 1
Efficient Frontiers of Nominal Farmland Return with Different Holding Periods



The correlations of the time-series residuals are estimated using the Gaussian copula.

Farmland-Only Portfolio Results

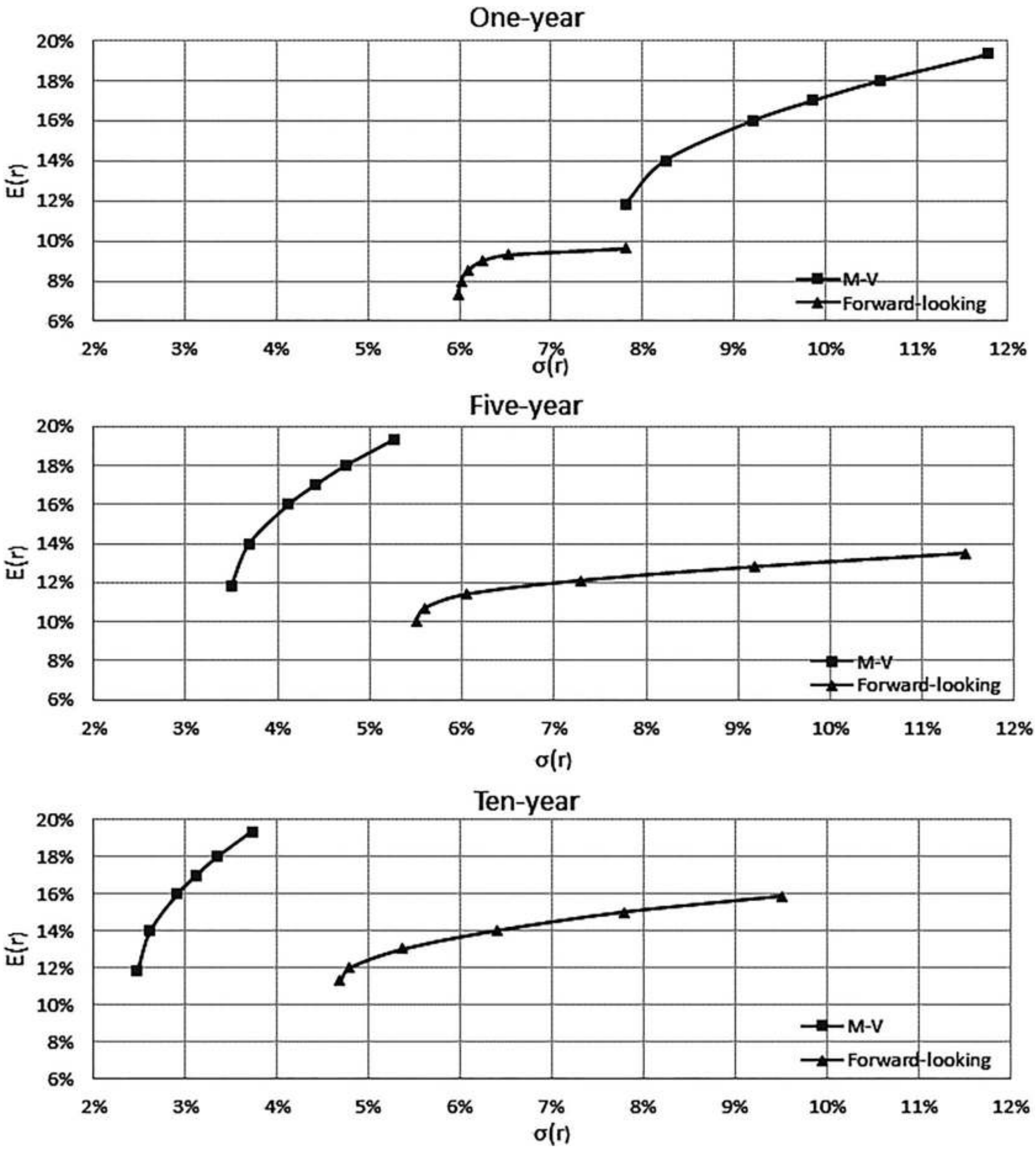
Figure 1 shows the efficient frontiers of forward-looking farmland portfolio nominal returns with different holding periods derived from the ARMA-copula model. For a given risk level, the expected return increases with the holding period. For the minimum-risk portfolios, the expected returns are 7.34%, 10.05%, and 11.27% for the one-year, five-year, and ten-year holding periods, respectively.[9] The minimum risk decreases with a longer holding period. The minimum volatilities are 5.99%, 5.50%, and 4.68% for the one-year, five-year, and ten-year holding periods, respectively.

Figure 2 compares the efficient frontiers of nominal returns derived from the ARMA-copula model and from the M-V approach for one-year, five-year, and ten-year holding periods. The inputs for the M-V approach are a historical sample mean and variance-covariance with the implicit assumption that returns are independent across time. The expected return based on the M-V approach is identical across different holding periods. The standard deviation decreases with a longer holding period, due to diversification over time, as measured by the square root of the length of the holding period. By contrast, the expected return, implied by the ARMA-copula model, varies across different holding periods due to the time-varying expected return. The standard deviation for a longer holding period does not decrease as much as in the M-V approach because of the autocorrelation in the return series. These results indicate that the time-varying expected return and autocorrelation in the return series have important implications on the risk-return profile of farmland investment.

The ARMA-copula results show that the superior performance predicted by the M-V approach should be treated with caution. First, the high expected return can be achieved only with a long holding period. The graphs in Figure 2 show that for a one-year holding period, the forward-looking expected return is much lower than the M-V approach implies. The forward-looking expected return is closer to the historical average for a five-year holding period and becomes comparable for a ten-year holding period. Second, the forward-looking risk involved in farmland investment is not as

[9] Note we do not take property tax or transaction costs into account.

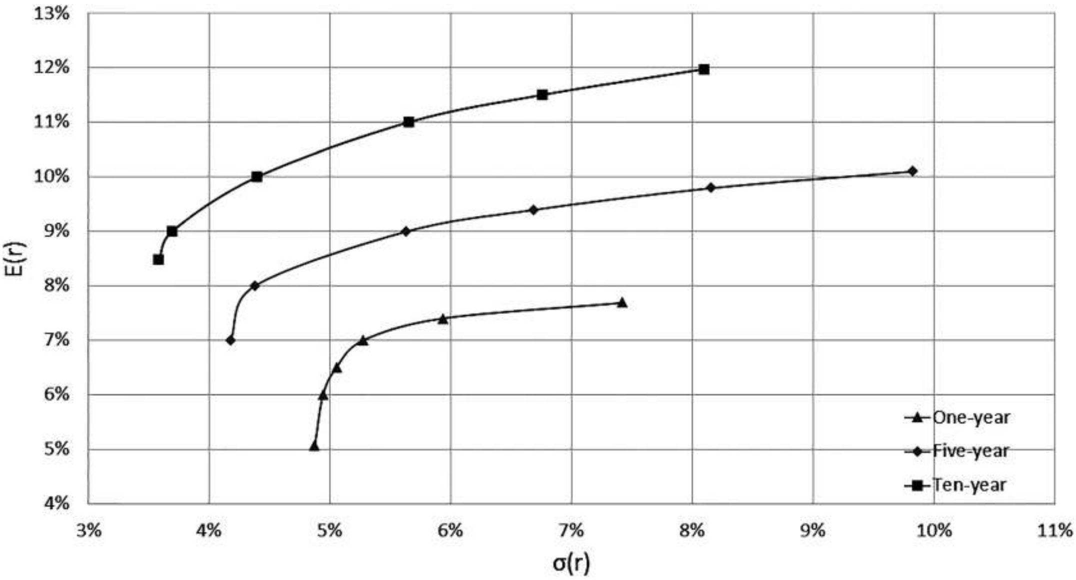
Figure 2
Efficient Frontiers of Nominal Farmland Return as Implied by the ARMA-Copula Model and the M-V Method



low as implied by the M-V approach for long holding periods. This is true because the diversification effect over time is offset by the autocorrelation in the return series. Figure 2 shows that the forward-looking standard deviation is lower than the M-V value for a one-year holding period; however, it is higher than the M-V value for the five-year and ten-year holding periods. In summary, from a forward-looking perspective, while the high expected return can be achieved only with long-term investment, the risk involved with the long holding period is also relatively high.

Similar results are observed for real farmland returns. Figure 3 shows the efficient frontiers of forward-looking real returns with dif-

Figure 3
Efficient Frontiers of Real Farmland Return with Different Holding Periods



ferent holding periods. For a given risk level, the expected real return increases with the holding period. For the minimum-risk portfolios, the expected returns are 5.08%, 7.00%, and 8.48% for the one-year, five-year, and ten-year holding periods, respectively. The minimum risk decreases with a longer holding period. The minimum volatilities are 4.87%, 4.18%, and 3.58% for the one-year, five-year, and ten-year holding periods, respectively. These observations are consistent with the results for nominal returns.

Figure 4 compares the forward-looking efficient frontiers of real farmland return and the efficient frontiers as implied by the M-V approach. As was true with nominal returns, the forward-looking expected real return varies across different holding periods. For a given expected return level, volatility decreases for longer holding periods, but to a lesser degree as in the M-V approach. This reduced time diversification effect is due to the autocorrelation in the return series. These results indicate that the time-varying expected return and autocorrelation in the return series have similar implications on the risk-return profile for real returns as for nominal returns. That is, while the superior expected return predicted by the M-V approach can be attained only through a long holding period from a forward-looking perspective, the risk involved in the long holding period is much higher than implied by the M-V approach.

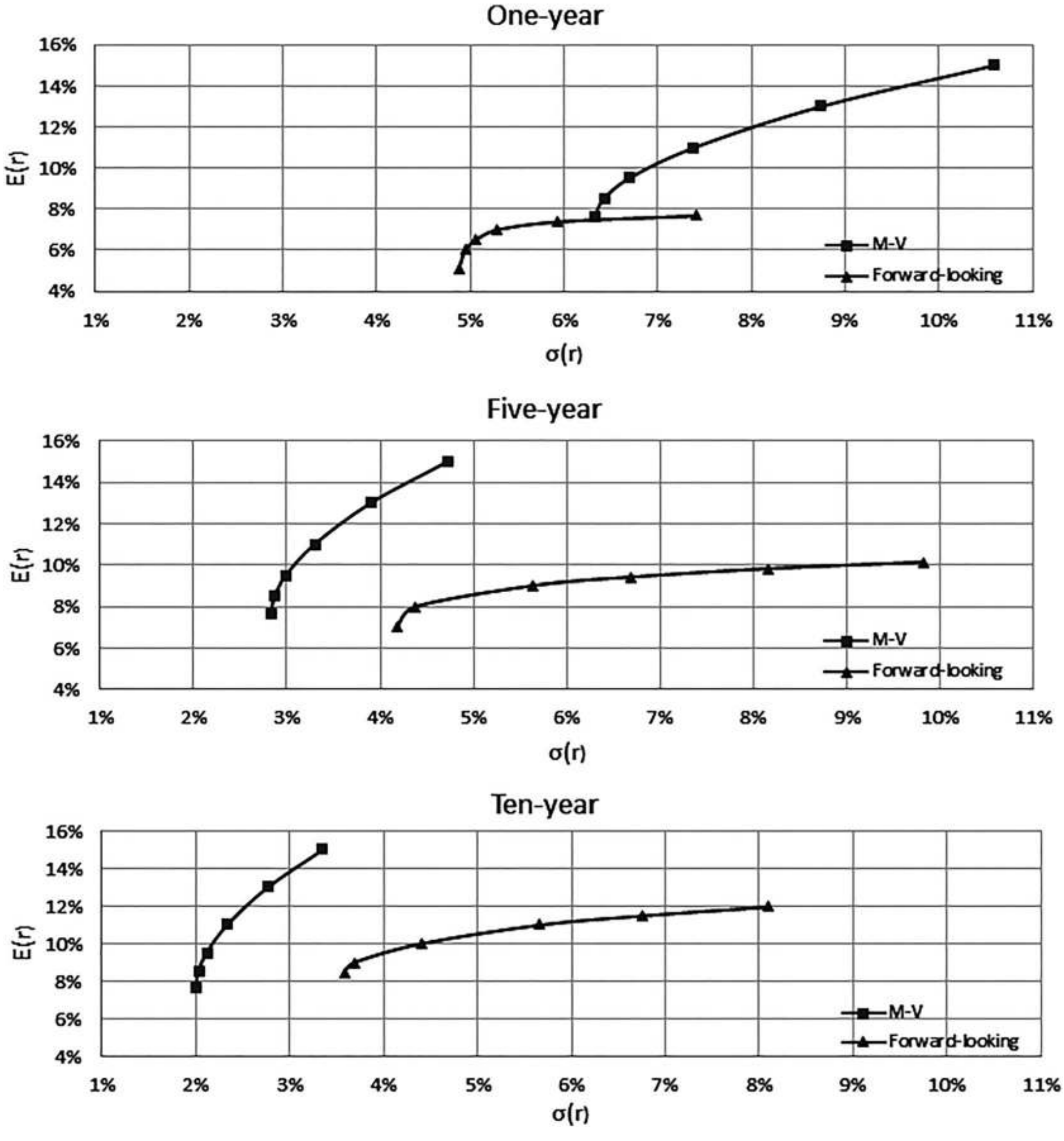
Mixed-Asset Portfolio Results

Investors typically hold mixed-asset portfolios and are interested in knowing the optimal allocation to each asset class (Scholtens and Spierdijk 2010). Therefore, this section discusses forward-looking farmland investment characteristics within a mixed-asset portfolio context. Farmland is treated as a separate asset class, and additional asset classes considered include common stocks, Treasury bonds, and corporate bonds. The white noise model is the fitted time-series model for these additional asset classes. As a result, their forward-looking expected return and volatility are equal to the historical sample mean and volatility.[10]

[10]A reviewer pointed out that within-year volatility also matters for calculating portfolio variance. Since low returns impact the weights down and high returns up, the asymmetry in weights may penalize higher-risk realizations. We acknowledge that this is a limitation to using annual returns to calculate portfolio variance.

Figure 4

Efficient Frontiers of Real Farmland Return as Implied by the ARMA-Copula Model and the M-V Method



With estimated marginal time series and correlation structure, the same methodology is used to construct optimal mixed-asset portfolios, as is true for the farmland-only optimal portfolios.

Table 2 presents the forward-looking optimal portfolios for the one-year, five-year, and ten-year holding periods, as well as the M-V optimal portfolios using nominal returns. For the one-year holding period, the allocation to farmland in the minimum-risk portfolio is substantial because of the low risk involved with farmland return in the short term. With increased risk tolerance for the one-year holding period, the allocation to farmland decreases due to the low expected return of farmland investment in the short term. While expected farmland return tends to rise for longer holding periods, the risk involved is also substantially increased. As a result, the

Table 2
Optimal Mixed-Asset Portfolios Using Nominal Returns

$E(r)$	$\sigma(r)$	CV	Sharpe Ratio	Farmland	Stocks	Treasury Bonds	Corporate Bonds
1-Year Holding Period							
6.47%	5.47%	0.85	0.30	0.32	0.04	0.00	0.65
7.68%	5.98%	0.78	0.48	0.25	0.18	0.23	0.34
8.88%	7.20%	0.81	0.56	0.19	0.33	0.48	0.00
10.09%	9.02%	0.89	0.58	0.01	0.48	0.50	0.00
11.29%	11.90%	1.05	0.54	0.00	0.74	0.26	0.00
12.50%	15.88%	1.27	0.48	0.00	1.00	0.00	0.00
5-Year Holding Period							
7.36%	2.90%	0.39	0.87	0.09	0.08	0.00	0.83
8.38%	3.09%	0.37	1.15	0.09	0.21	0.23	0.47
9.41%	3.50%	0.37	1.31	0.09	0.33	0.52	0.06
10.43%	4.28%	0.41	1.31	0.04	0.54	0.42	0.00
11.46%	5.58%	0.49	1.19	0.00	0.77	0.23	0.00
12.49%	7.17%	0.57	1.07	0.00	1.00	0.00	0.00
10-Year Holding Period							
7.43%	2.09%	0.28	1.24	0.06	0.08	0.00	0.86
8.45%	2.21%	0.26	1.63	0.07	0.21	0.23	0.49
9.47%	2.49%	0.26	1.86	0.07	0.33	0.52	0.08
10.49%	3.03%	0.29	1.87	0.05	0.54	0.41	0.00
11.50%	3.97%	0.35	1.68	0.03	0.77	0.20	0.00
12.52%	5.09%	0.41	1.51	0.00	1.00	0.00	0.00
M-V Approach							
9.63%	4.54%	0.47	1.06	0.39	0.00	0.00	0.61
10.21%	4.82%	0.47	1.11	0.49	0.03	0.02	0.46
10.79%	5.47%	0.51	1.09	0.56	0.09	0.12	0.24
11.37%	6.33%	0.56	1.03	0.63	0.14	0.23	0.00
11.95%	7.48%	0.63	0.95	0.72	0.18	0.10	0.00
12.52%	16.22%	1.30	0.47	0.00	1.00	0.00	0.00

Note: CV, coefficient of variation.

allocations to farmland for the five-year and ten-year holding periods are lower than for the one-year holding period, due to the large risk involved in long-term farmland investment. The percentage of farmland in optimal portfolios at all risk levels is less than 10% for the five-year and ten-year holding periods. By contrast, substantial allocations to farmland are observed in optimal portfolios using the M-V approach because of the superior historical risk-return profile. These large allocations to farmland, however, are not supported by the analysis from a forward-looking perspective.

Similar results are observed for the mixed-asset portfolios using real returns, and the results are reported in Table 3. The allocation to farmland for the one-year holding period is substantial for a low risk level. Increasing risk tolerance reduces allocations to farmland for the one-year holding period because of the low expected farmland return in the short term. For the five-year and ten-year holding periods, the percentage of farmland in optimal portfolios at all risk levels is quite low due to the significant amount of risk involved in farmland return in the long run. The M-V approach, however, still implies substantial allocations to farmland at all risk levels that are not supported from a forward-looking perspective.

The mixed-asset portfolio results are predicated on the assumption that all asset classes are held for the same length of time. If farmland is held for longer periods than the other

Table 3
Optimal Mixed-Asset Portfolios Using Real Returns

E(*r*)	*σ*(*r*)	CV	Sharpe Ratio	Farmland	Stocks	Treasury Bonds	Corporate Bonds
1-Year Holding Period							
3.47%	5.37%	1.55	0.50	0.39	0.02	0.00	0.60
4.46%	6.04%	1.35	0.61	0.31	0.20	0.16	0.34
5.46%	7.55%	1.38	0.62	0.23	0.38	0.39	0.00
6.45%	9.67%	1.50	0.59	0.06	0.56	0.38	0.00
7.45%	12.32%	1.65	0.54	0.00	0.78	0.22	0.00
8.44%	15.60%	1.85	0.49	0.00	1.00	0.00	0.00
5-Year Holding Period							
4.08%	2.91%	0.71	1.14	0.10	0.06	0.00	0.85
4.95%	3.16%	0.64	1.32	0.10	0.23	0.12	0.55
5.82%	3.69%	0.63	1.37	0.11	0.39	0.44	0.06
6.69%	4.52%	0.68	1.31	0.07	0.59	0.34	0.00
7.56%	5.69%	0.75	1.19	0.03	0.79	0.18	0.00
8.43%	7.05%	0.84	1.09	0.00	1.00	0.00	0.00
10-Year Holding Period							
4.12%	2.10%	0.51	1.59	0.06	0.06	0.00	0.88
4.99%	2.27%	0.45	1.86	0.07	0.23	0.12	0.58
5.86%	2.64%	0.45	1.93	0.08	0.38	0.43	0.10
6.73%	3.20%	0.48	1.86	0.07	0.58	0.35	0.00
7.60%	4.02%	0.53	1.70	0.06	0.78	0.16	0.00
8.47%	5.00%	0.59	1.54	0.00	1.00	0.00	0.00
M-V Approach							
6.02%	4.42%	0.73	1.19	0.45	0.00	0.00	0.55
6.53%	4.61%	0.71	1.25	0.54	0.01	0.00	0.44
7.03%	5.10%	0.73	1.23	0.62	0.05	0.03	0.30
7.53%	5.75%	0.76	1.17	0.68	0.10	0.14	0.08
8.04%	6.55%	0.81	1.11	0.76	0.13	0.11	0.00
8.54%	8.01%	0.94	0.97	1.00	0.00	0.00	0.00

Note: CV, coefficient of variation.

asset classes, the optimal weight of farmland in a mixed-asset portfolio may be higher given that the risk of other asset classes increases due to lower diversification over shorter times. The analysis for portfolio components with unequal holding periods is beyond the scope of this paper.

4. Limitations of This Research

As mentioned earlier, the data are for 15 states for the period 1967–2017 and are from the USDA National Agricultural Statistics Service (NASS) database. Results do not extend to other states or to different time periods. The NASS data are from a June survey of landowners and may not provide an accurate representation of actual returns obtained by investors or landowners. An alternative measure based on returns to institutional investors in farmland[11] is available from the National Council of Real Estate Investment Fiduciaries, though for a shorter time period. The NASS data exclude property taxes. Our measured returns on alternative investments in common stocks, Treasury bonds, and corporate bonds assume a passive investment strategy and are measured annually. Returns to actively managed portfolios will be much more volatile. Finally, we should mention that there may well be other reasons such as high transactions costs and a lengthy investment horizon for land, as

[11] See https://www.ncreif.org/data-products/farmland/.

well as different tax treatment, that may also explain the high-return/low-risk phenomena.

5. Conclusions

The ARMA-copula model proposed in this article can serve as a tool for forward-looking farmland portfolio management by taking into account autocorrelation and time-varying patterns in farmland returns. The optimal portfolio is constructed based on projected future returns instead of historical values. We show that the forward-looking risk-return profile is significantly different than the historical profile for both nominal and real returns. While the superior historical return level can be expected only through long-term investments, the risk involved in the long investment period is significantly higher than the historical sample volatility.

Within a mixed-asset portfolio context, our results show that the allocations to farmland assets are much lower from a forward-looking perspective than the M-V approach implies. Again, the autocorrelation in farmland return series increases the risk involved in long-term farmland investments, which results in a lower diversification effect over time for farmland assets than for the other traditional investment assets. The allocations to farmland in mixed-asset optimal portfolios, therefore, are quite small in spite of the superior historical risk-return profile of farmland assets. These results shed light on the high-return/low-risk paradox in the existing land value literature.

While the analysis in this paper is intended to provide guidance for passive investors holding farmland assets in their investment portfolios, it may not apply to farmers who own and farm land. The high entry and exit costs of farming can deter farmers from frequently trading in and out of farmland. We also acknowledge that the need to use a forward-looking perspective is just one of many considerations that investors should use to evaluate the role of farmland in portfolio management.

Future research could explore farmland risk-return characteristics from an asset-pricing viewpoint. If the forward-looking investment risk caused by the autocorrelation in farmland return series has been appropriately priced in comparison with other investment alternatives, the superior historical farmland returns might be justified. The analysis in this article shows that this "autocorrelation risk" is low in the short term but tends to increase dramatically with extended holding periods. Given the illiquidity, indivisibility, and high transaction costs associated with farmland investment, a long holding period may be selected by most investors. This is when the autocorrelation risk becomes significant.

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