Money Supply, Capital Market Factors, and Farmland Return Prediction: An Artificial Neural Network Approach

Farmland value slightly increased in 2017 even though farm income was lower. This development suggests the rate of return required by investors for farmland asset has been reduced. A similar phenomenon has been observed in the equity market which also suggests reduced equity risk premium. One possible explanation for the decreasing required rate of return is an increased money supply caused by the Federal Reserve's large-scale asset purchases. Previous research suggests that the money supply affects several macroeconomic risk factors through different transmission channels, which in turn influence investor behaviors and asset returns. This article examines the predictive power of these risk factors for farmland asset returns. Both linear and neural network models are used and the forecast accuracy is compared across different models. The results indicate that farmland return prediction is significantly improved by adding capital market excess return as an explanatory variable. Adding additional risk factors, however, does not improve the prediction with the sample used in this study.

Introduction

Farmland accounts for over 80 percent of the total value of a typical farmer's portfolio (Economic Research Service, 2016). Farmland returns therefore greatly impact the financial well-being of the nation's agricultural sector. The attractive risk-return profile also makes farmland a favorable potential asset class for an investment portfolio (Noland *et al.*, 2011; Chen *et al.*, 2015). This important role of farmland assets has generated a large literature on farmland returns. Barry (1980) first analyzed farmland returns using market portfolio return as the only risk factor. The author found that farmland assets added insignificant systematic risk to a well-diversified investment portfolio. Several studies extended Barry's work by applying multifactor asset pricing models that included a set of risk factors beyond market portfolio return (see, among others, Arthur, Carter, and Abizadeh, 1988; Irwin, Forster, and Sherrick, 1988; Bjornson, 1995; Kuethe, Hubbs, and Morehart, 2014). The risk factors are either explicit macroeconomic variables or implicit principle components extracted from observable variables. Moss and Katchova (2005) summarized the findings on the relationship between farmland return and market factors, concluding that while farmland assets exhibit low systematic risk, farmland return is sensitive to several financial market risk factors.

After a decline in 2016, average US farmland value increased slightly in 2017. Farm income, however, has declined and is still under stress following a record high in 2013. The relationship between farmland price and the income produced by the farmland can be expressed by the capitalization model $P = I/(r - g)$, where P represents the farmland price, I the farmland income, r the discount rate, and g the income growth rate. When the farmland income is decreasing, an increase in farmland price, according to the capitalization model, can potentially be caused by a lowered discount rate. The discount rate represents the opportunity cost or required rate of return for investors to invest in farmland. This rate can be thought of as the risk-free rate plus a risk premium associated with farmland investment. Given that the risk-free rate has been low after the 2007-09 financial crisis, the decreased discount rate perhaps indicates that investors now require lower rate of return or risk premium on farmland investment. The same "low income high asset price" phenomenon has also been observed in the equity market. The S&P 500 index level has increased significantly in 2017 as has the price to earnings ratio[1]. This shows that investors are accepting of a lower risk premium in equity investments.

One possible explanation for the decreasing required rate of return is an increased money supply. At the end of year 2008 when federal funds rate as the traditional monetary policy target reached its lower bound of zero, the Federal Reserve started to implement a large-scale asset purchase program by purchasing substantial quantities of medium- and long-maturity assets. Holdings of the assets by private investors were replaced by short-term, risk-free bank reserves which increased the total money supply in the economy. Figure 1 and 2 show the broad money supply (M2) and the money to GDP ratio in the US starting from 2007 respectively. The increased money supply potentially impacted several macroeconomic factors and potentially changed investor behavior. According to Gagnon *et al.* (2010), the first macroeconomic factor being impacted by increased money supply is the risk premium on the assets that the Fed purchased as well as other related assets via the portfolio balance effect (Tobin, 1958). By purchasing a particular asset, the Federal Reserve reduces the aggregate supply for particular assets. In market equilibrium, the risk premium then must adjust to match aggregate demand with the decreased aggregate supply. In order for investors to adjust their required rate of return, the expected return on the purchased and other assets has to fall. As Emmerling, Jarrow, and Yildirim (2015) indicate, the purchases by the Federal Reserve bid up the price and the realized return of the purchased assets, which in turn lowered the expected return of the asset. Investors' required rate of return therefore has to decline. These effects are not only imposed on the assets being purchased but also spill over onto other assets through portfolio rebalancing by investors. Besides the risk premium, the increased money supply also has impacts on other macroeconomic risk factors such as the interest rate term spread and corporate credit spread (Gagnon *et al.*, 2010; Gilchrist and Zakrajsek, 2013).

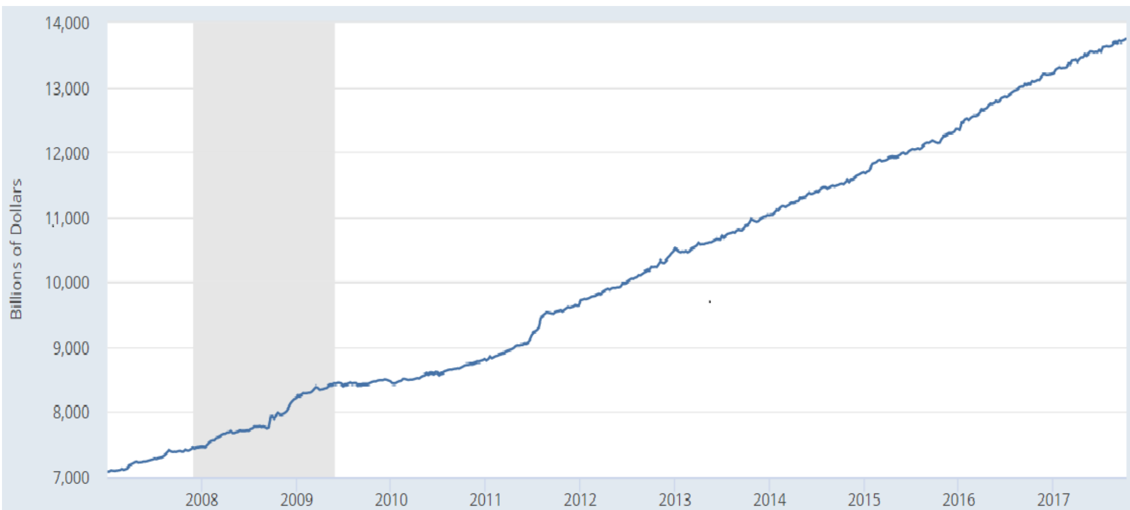

Figure 1. Broad money supply (M2) in the US. Source: Board of Governors of the Federal Reserve System (US).

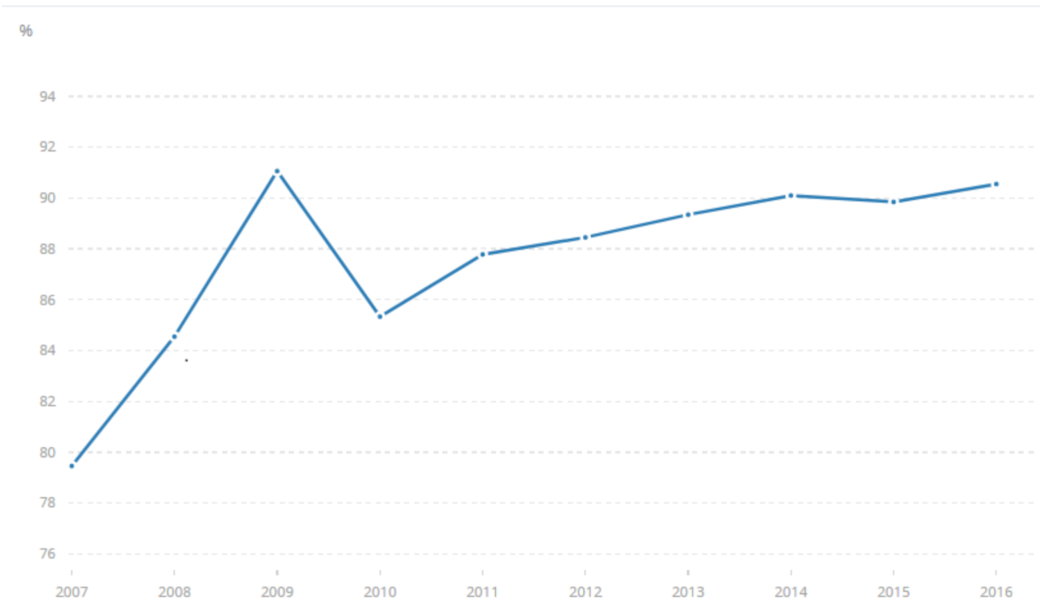

Figure 2. Broad money supply (M2) as a percentage of total GDP in the US. Source: World Bank Open Data.

In this article, we investigate the predictive power of these risk factors for farmland asset returns. We assume farmland returns follow an autoregressive process with expected farmland return as the mean value. Investors' demand drives the expected return towards required rate of return which is affected by the macroeconomic risk factors. We first examine three linear models: a univariate time-series model, a one-factor model using capital market risk premium as the single risk factor[2], and a three-factor model taking on additional risk factors that are also affected by increased money supply. In addition, the forecast accuracy of the three linear models is compared with that of their artificial neural network counterparts that use the same predictors. The neural network model imitates the nonlinear, parallel information processing structure of human brain network (McNelis, 2005). By allowing for a more flexible functional relationship between predicted variables and predictors, the neural network model relaxes the linearity assumption and captures potentially undetected regularities in asset price and return movements (Kostov, Patton, and McErlean, 2008; White, 1989).

Our study focuses on state-level cropland returns across 15 major agricultural producing states in the US. The annual land return, spanning the period 1968-2016, is calculated as the sum of cash rental income and capital appreciation divided by land value. A rolling estimation forecasting procedure is used to generate forecasts of annual land returns for each of the 15 states. Each forecast is based on models estimated using the data from previous 41 years. Forecasts of land returns from 2008 to 2016 are generated and compared to actual returns. The sum of squared errors (SSE) is calculated to assess forecast accuracy for each state. Results indicate that each neural network model provides lower SSE than the corresponding linear model for all the states. More importantly, while adding market risk factors seems not to help for some states using linear models, it becomes helpful and improves the prediction under the neural network framework.

A formal comparison of the forecast accuracy between different models is conducted using a paired sample t-test. It turns out that the one-factor model with the excess market return factor included is the best performing model under both linear and neural network frameworks. In addition, the one-factor neural network model significantly outperforms its linear counterpart. These results indicate that the excess market return factor could provide information that significantly improves farmland return prediction. This may offer help for farmers to plan future agricultural production and decision makers to resolve agricultural policy issues given the significant role of farmland assets in the agricultural sector. There is no empirical evidence, however, that the other two risk factors add useful information to predict farmland returns.

Theoretical Framework

Due to the potential autocorrelation in farmland return series (Moss, Featherstone, and Baker, 1987), we start by assuming farmland return follows an autoregressive process with lag order 1 (AR(1))[3].

(1) $R_t - E(R) = \beta_0 + \varphi * [R_{t-1} - E(R)] + \varepsilon_t,$

where R_t represents the farmland return at time t and $E(R)$ represents expected farmland return. By rearranging equation (1) we obtain

(2) $R_t = \beta_0 + (1 - \varphi) * E(R) + \varphi * R_{t-1} + \varepsilon_t,$

We then assume that farmland asset supply is fixed at Q_s. Farmland asset is demanded by farmers to produce crop products and by investors to gain investment returns. Farmers derive their demand function from expected farmland return, denoted by $Q_{d,f}(E(R))$[4]. As indicated by Frankel and Dickens (1983), investors' demand for an asset is related to the expected return of the asset and their risk premium for risky asset investment. Following this approach, we assume an investor's demand function for farmland takes the form of $Q_{d,i}(E(R), RP)$, where RP is the risk premium associated with risky asset investment. Under equilibrium where total demand equals supply, the following equation holds,

(3) $Q_s = Q_{d,f}(E(R)) + Q_{d,i}(E(R), RP).$

Supposing $E(R)$ can be solved out from equation (3), the following equation can be obtained,

(4) $E(R) = f(Q_s, RP).$

For any risky asset investment, a risk premium would be needed to compensate an investor for holding the risky assets. Excess money supply could change an investor's risk premium through the portfolio balance effect. By bidding up asset price, the excess money supply increases realized return and reduces investors' risk premium over future periods (Emmerling, Jarrow, and Yildirim, 2015). In the absence of data on investors' risk premium level, we use realized capital market excess return in the previous period as an indicator for current risk premium level required by investors. So we rewrite equation (4) as

$$(5) \quad E(R) = f(Q_s, R_m - R_f),$$

where $R_m - R_f$ is realized excess market return in the previous period.
Substituting equation (5) into equation (2) we have

$$(6) \quad R_t = \beta_0 + (1 - \varphi) * f(Q_s, (R_m - R_f)_{t-1}) + \varphi * R_{t-1} + \varepsilon_t.$$

Besides the risk premium for risky asset investments, increased money supply has been shown to have impacts on other macroeconomic risk factors such as the interest rate term spread and corporate credit spread (Gagnon *et al.*, 2010; Gilchrist and Zakrajsek, 2013). Assuming an investor's demand for farmland is also driven by these risk factors, we can rewrite an investor's demand function as $Q_{d,i}(E(R), RP, \gamma_1, \ldots, \gamma_n)$, where $\gamma_1, \ldots, \gamma_n$ represent the additional n macroeconomic risk factors. Following this new demand function, equation (5) and (6) can then be rewritten as

$$(7) \quad E(R) = f(Q_s, R_m - R_f, \gamma_1, \ldots, \gamma_n),$$

$$(8) \quad R_t = \beta_0 + (1 - \varphi) * f(Q_s, (R_m - R_f)_{t-1}, \gamma_{1,t}, \ldots, \gamma_{n,t}) + \varphi * R_{t-1} + \varepsilon_t.$$

Models

Three linear models and three artificial neural network models are considered and compared for their predictive ability. The three linear models consist of a univariate time-series model, a one-factor model, and a three-factor model. The three neural network models use exactly the same predictors as the linear models but have a different non-linear functional form.

The first linear model is built from equation (2) by assuming farmland return simply follows an AR(1) process with a constant expected value,

$$(9) \quad R_t = \beta_0 + \varphi R_{t-1} + \varepsilon_t,$$

where R_t denotes the farmland return at time t and R_{t-1} denotes the farmland return at time $t-1$. For convenience, this model is labeled as Model 1.

The second linear model is derived from equation (6) by assuming the farmer's demand function $Q_{d,f}(\cdot)$ and the investor's demand function $Q_{d,i}(\cdot)$ are both linear. As a result, the function $f(\cdot)$ in equation (6) is in a linear form. Denoting the excess market return at time t as $\gamma_{m,t}$, the model can be described as

$$(10) \quad R_t = \beta_0 + \varphi R_{t-1} + \beta_m \gamma_{m,t-1} + \varepsilon_t.$$

This one-factor linear model is referred to as Model 2.

The third linear model is derived from equation (8) by assuming again the farmer's demand function and the investor's demand function are both linear. Function $f(\cdot)$ is therefore also linear and two additional risk factors beyond excess market return are included. The two additional risk factors are the bond term spread (TERM) and the economy-wide default risk (DEFAULT). The TERM factor is calculated as the difference between ten-year and one-year Treasury bond yields. The DEFAULT factor is calculated as the difference between long-term BAA- and AAA-rated corporate bond yields. The model can be written as

$$(11) \quad R_t = \beta_0 + \varphi R_{t-1} + \beta_m \gamma_{m,t-1} + \beta_1 \gamma_{1,t} + \beta_2 \gamma_{2,t} + \varepsilon_t,$$

where $\gamma_{1,t}$ denotes the TERM factor and $\gamma_{2,t}$ the DEFAULT factor at time t. We refer this three-factor linear model as Model 3.

Neural network models relax the linearity assumption and potentially increase the flexibility of the demand functions. Similar to linear models, a neural network builds up functional relationships between a set of input variables and one or more output variables. The difference between linear models and neural network models is that the neural network model uses hidden layers to link input and output variables. Input variables are transformed by an activation function in the hidden layer and then connected to the output variables, in a similar way that the human brain processes information. This hidden layer processing method represents an efficient way to model nonlinear relationships (McNelis, 2005). In addition, it has been shown that given sufficiently many hidden-layer units, a three-layer (input, output, and hidden layers) neural network can approximate any continuous functions arbitrarily well (Bengio, Goodfellow, and Courville, 2015). For a three-layer neural network, each input-layer variable has a weighted connection to each hidden-layer unit, and each hidden-layer unit has a weighted connection to the output-layer variable. Using the logistic activation function to transform the input variables, the generic three-layer neural network model can be formally written as

$$(12) \quad n_{j,t} = \beta_{j,0} + \sum_{i=1}^{i^*} \beta_{j,i} x_{i,t},$$

$$(13) \quad N_{j,t} = logsig(n_{j,t}) = \frac{1}{1 + exp(-n_{j,t})},$$

$$(14) \quad y_t = \alpha_0 + \sum_{j=1}^{j^*} \alpha_j N_{j,t},$$

where y is the output variable, $[x_1, \ldots, x_{i^*}]$ is the vector of input variables, $[N_1, \ldots, N_{j^*}]$ is the vector of hidden-layer units, $[\alpha_0, \alpha_1, \ldots, \alpha_{j^*}]$ is the vector of weights connecting the hidden-layer units to the output variable, and $[\beta_{j,0}, \beta_{j,1}, \ldots, \beta_{j,i^*}]$ is the vector of weights connecting input variables to the jth hidden-layer unit.

The neural network models that correspond to the three linear models defined previously can thus be described as

$$(15) \quad R_t = \alpha_0 + \sum_{j=1}^{j^*} \alpha_j logsig(\beta_{j,0} + \varphi_j R_{t-1}) + \varepsilon_t,$$

$$(16) \quad R_t = \alpha_0 + \sum_{j=1}^{j^*} \alpha_j logsig(\beta_{j,0} + \varphi_j R_{t-1} + \beta_{j,m}\gamma_{m,t-1}) + \varepsilon_t,$$

$$(17) \quad R_t = \alpha_0 + \sum_{j=1}^{j^*} \alpha_j logsig(\beta_{j,0} + \varphi_j R_{t-1} + \beta_{j,m}\gamma_{m,t-1} + \beta_{j,1}\gamma_{1,t} + \beta_{j,2}\gamma_{2,t}) + \varepsilon_t,$$

These three neural network models are labeled as Model 4, Model 5, and Model 6 respectively.

Empirical Analysis

We focus on annual state-level cropland returns in 15 major agricultural producing states in the US. The land return is calculated as the sum of cash rental income and capital appreciation divided by land value. Historical data of the cash rental income and land value were collected from the USDA National Agricultural Statistics Service (NASS) databases, spanning from 1968 to 2016. The excess market return data were gathered from the Center for Research in Security Prices on Kenneth French's website[5]. The maturity risk (TERM) and default risk (DEFAULT) data were obtained from the Federal Reserve Bank of St Louis database.

Sum of Squared Errors

A rolling estimation forecasting procedure is used to generate forecasts of land returns in 2009-2016 for each state. We generate each forecast based on models estimated using the data from previous 41 years. That is, we use the data from 1968 to 2008 to generate forecast of land return in 2009, the data from 1969 to 2009 to generate forecast for 2010, and so on. The Sum of Squared Errors (SSE) is used as a measure to assess forecast accuracy of different models:

$$(18)\quad SSE = \sum_{i=1}^{n} (\hat{R}_i - R_i)^2,$$

where n is the total number of forecasts generated, $\hat{R}_i$ is the ith predicted return, and R_i is the ith realized return.

Table 1 reports the SSE of predicted farmland returns for each of the 15 states using different models. Among the linear models (Model 1 through Model 3), adding market factors improves forecast accuracy for eight out of the 15 states. Specifically, the one-factor model provides the most accurate prediction for seven states and the three-factor model outperforms the one-factor model for only one state among the eight states for which market factors improve the prediction. For the remaining seven states, the best linear model is the univariate time-series model.

All the neural network models provide lower SSE than their linear counterparts for all the 15 states. More importantly, the market factors turn out to play more significant roles within the neural network models. Forecast accuracy is improved for 12 out of the 15 states after market factors being included. In addition, the three-factor neural network model outperforms the one-factor neural network model for eight states among the 12 states for which market factors improve the prediction. These results show that the more flexible neural network models seem to capture market information more efficiently than linear models. While market factors seem not useful for predicting farmland return in some states using traditional linear models, market factors become helpful under the neural network framework.

Table 1. The sum of squared errors of predicted farmland returns for individual states

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Arkansas	0.0046	0.0059	0.0092	0.0039	0.0051	0.0048
Illinois	0.0672	0.0675	0.0683	0.0541	0.0591	0.0498
Indiana	0.0690	0.0632	0.0758	0.0671	0.0575	0.0587
Iowa	0.1216	0.1153	0.1336	0.1160	0.1012	0.1087
Kansas	0.0678	0.0680	0.0785	0.0645	0.0622	0.0601
Louisiana	0.0223	0.0230	0.0301	0.0207	0.0199	0.0198
Michigan	0.0336	0.0337	0.0339	0.0315	0.0296	0.0295
Minnesota	0.0638	0.0616	0.0915	0.0625	0.0544	0.0594
Mississippi	0.0191	0.0248	0.0499	0.0180	0.0210	0.0195
Missouri	0.0246	0.0235	0.0288	0.0237	0.0198	0.0187
North Dakota	0.1561	0.1576	0.1939	0.1310	0.1317	0.1352
Ohio	0.0386	0.0371	0.0390	0.0378	0.0358	0.0315
South Dakota	0.0934	0.0926	0.1207	0.0904	0.0844	0.0855
Texas	0.0393	0.0393	0.0355	0.0352	0.0304	0.0299
Wisconsin	0.0234	0.0209	0.0235	0.0216	0.0178	0.0173

Paired Sample t-test

A paired sample t-test (Ramsey and Schafer, 2012) is conducted to formally compare the forecast accuracy of different models using samples from all the 15 states as a whole. The paired sample t-test is a statistical procedure used to determine whether the mean difference between two sets of observations is zero. The null hypothesis assumes the true mean difference is equal to zero.

The first sample group we use for the t-test is the squared deviations of predicted returns from the corresponding realized returns, normalized by the square of realized returns to account for varying return levels across states. Specifically, for the ith forecast of farmland return in the jth state, the squared error is calculated as $[(\hat{R}_{ij} - R_{ij})/R_{ij}]^2$, where $\hat{R_{ij}}$ is the predicted farmland return and R_{ij} is the realized return. To evaluate if there is any incremental value by adding market risk factors, the following null hypotheses are tested.

H1: The univariate time-series model and the one-factor model provide no forecasting accuracy difference under the linear framework.

H2: The one-factor model and the three-factor model provide no forecasting accuracy difference under the linear framework.

H3: The univariate time-series model and the one-factor model provide no forecasting accuracy difference under the neural network framework.

H4: The one-factor model and the three-factor model provide no forecasting accuracy difference under the neural network framework.

Table 2 presents the t-test results. Among the linear models, the one-factor model outperforms the univariate time-series model significantly. However, the difference between the one-factor model and the three-factor model is not significant. The t-score shows that the three-factor linear model provides even lower forecast accuracy than the one-factor linear model, although the difference is not statistically significant. This indicates that the additional risk factors beyond excess market return may not add more useful information for predicting future farmland returns. Based on these results, hypothesis H1 can be rejected but there is not enough support to reject hypothesis H2.

For the neural network models, similar results are observed. Adding a single excess market return factor lowers forecast error and improves the forecast accuracy significantly. While adding the two additional market risk factors also leads to lower forecast error, the difference is not statistically significant. Again, we reject hypothesis H3 but fail to reject hypothesis H4. All these results indicate that while the excess market return factor adds useful information for farmland return prediction, the other two market risk factors seem not helpful under either linear or neural network framework. Therefore, in terms of which market factors provide the most accurate forecast, the best model turns out to be the one-factor model with the excess market return factor included.

Table 2. Paired t-test results on forecast accuracy between different models with the first sample set

	t-score	p-value
Linear Model Comparisons		
Model 1 vs. Model 2	2.5148	0.0132*
Model 2 vs. Model 3	-1.3866	0.1682
Neural Network Model Comparisons		
Model 4 vs. Model 5	2.2279	0.0278*
Model 5 vs. Model 6	0.7947	0.4284

*Significance at the 95% level

To evaluate the effectiveness of the neural network models relative to their linear counterparts, the following hypotheses are also tested.

H5: The linear univariate time-series model and the corresponding neural network model provide no forecasting accuracy difference.

H6: The linear one-factor model and the corresponding neural network model provide no forecasting accuracy difference.

H7: The linear three-factor model and the corresponding neural network model provide no forecasting accuracy difference.

Table 3 presents the t-test results for the above hypotheses. A comparison between the linear and the neural network models shows that all the neural network models provide higher forecast accuracy than the corresponding linear models. However, only for the one-factor model does the neural network improve the forecast accuracy significantly. Thus only hypothesis H6 is rejected while hypotheses H5 and H7 cannot be rejected. As the one-factor model has shown to be the best model in terms of which risk factors to be included, the implication is that the use of neural networks improves farmland return forecast accuracy compared to linear models. This demonstrates the superiority of the neural network approach relative to linear models in predicting farmland asset returns.

Table 3. Paired t-test results on forecast accuracy between linear and neural network models with the first sample set

	t-score	p-value
Linear versus Neural Network Model Comparisons		
Model 1 vs. Model 4	0.6791	0.4984
Model 2 vs. Model 5	2.0750	0.0401*
Model 3 vs. Model 6	1.3055	0.1942

*Significance at the 95% level

The second sample set used for the t-test is the absolute value of normalized deviations of predicted returns from the corresponding realized returns. For the ith forecast of farmland return in the jth state, the absolute error is calculated as $\left|(\hat{R}_{ij} - R_{ij})/R_{ij}\right|$, where $\hat{R_{ij}}$ is the predicted farmland return and R_{ij} is the realized return. The same null hypotheses are tested with this new sample set.

Table 4 presents the t-test results with the new sample set. Again, the linear one-factor model outperforms the linear univariate time-series model significantly. In addition, the linear one-factor model also outperforms the linear three-factor model significantly. This indicates that while adding the excess market return factor improves the forecast accuracy, adding the additional risk factors actually hurts the forecast accuracy. Based on these results, hypothesis H1 and H2 are rejected; the best linear model is the one-factor model with the excess market return factor included.

In terms of the neural network models, adding a single excess market return factor lowers forecast error and improves the forecast accuracy significantly. Adding the two additional market risk factors seems to lower the forecast error, but the difference is not statistically significant. Thus, we reject hypothesis H3 but fail to reject hypothesis H4. The testing conclusion with the second sample set is again that while the excess market return factor improves farmland return prediction, the other two risk factors do not help. Under both the linear and the neural network framework, the best model is the one-factor model with the excess market return factor included.

Table 4. Paired t-test results on forecast accuracy between different models with the second sample set

	t-score	p-value
Linear Model Comparisons		
Model 1 vs. Model 2	2.7199	0.0075*
Model 2 vs. Model 3	-3.3811	0.0010*
Neural Network Model Comparisons		
Model 4 vs. Model 5	3.1570	0.0020*
Model 5 vs. Model 6	0.1830	0.8551

*Significance at the 95% level

To evaluate the effectiveness of the neural network models relative to their linear counterparts, the following hypotheses are also tested.

H5: The linear univariate time-series model and the corresponding neural network model provide no forecasting accuracy difference.

H6: The linear one-factor model and the corresponding neural network model provide no forecasting accuracy difference.

H7: The linear three-factor model and the corresponding neural network model provide no forecasting accuracy difference.

Table 5 presents the t-test results for the above hypotheses with the second sample set. The comparison between the linear and the neural network models again shows that all the neural network models provide higher forecast accuracy than the corresponding linear models. For both the one-factor model and the three-factor model, the neural network approach improves the forecast accuracy significantly. That is, hypotheses H6 and H7 are rejected in support of the neural network models. There is, however, not sufficient evidence to reject hypotheses H5. The testing results using the two sample sets consistently show the superiority of the neural network approach in farmland return predictions.

Table 5. Paired t-test results on forecast accuracy between linear and neural network models with the second sample set

	t-score	p-value
Linear versus Neural Network Model Comparisons		
Model 1 vs. Model 4	1.2884	0.2001
Model 2 vs. Model 5	3.5720	0.0005*
Model 3 vs. Model 6	2.9368	0.0040*

*Significance at the 95% level

Conclusions

Increased money supply affects several capital market risk factors which influence investor behaviors and asset returns. This article examines whether these risk factors are useful in farmland return prediction. We evaluate the predictive ability of these risk factors using both traditional linear models and advanced neural network approach. The results indicate that the one-factor model including excess market return significantly improves the forecast accuracy compared to the univariate time-series model that uses lagged farmland return as the only predictor. However, there is no significant difference in forecast accuracy between the one-factor model and the three-factor model with additional risk factors included. These observations apply consistently to both linear and neural network framework. In addition, we find that neural network models provide higher forecast accuracy than the corresponding linear models with the same explanatory variables. For the one-factor model, the improvement in forecast accuracy offered by neural network is statistically significant. This could be because the non-linear neural network structure captures market information in a more flexible and potentially more efficient way. For practical implications, the findings in this article suggest that farmers as well as policy makers can take advantage of market risk factors to make better future farmland return predictions.

[1]Historical data of the S&P 500 index level, dividend yield, and P/E ratio are available at www.multpl.com

[2]This factor is referred to as the "excess market return" for the rest of the article.

[3]ARMA(1,1), AR(1), MA(1), and white noise time-series models were all examined for fitness for the sample of farmland return series in each of the 15 states selected in this study. The AR(1) model was the best model for all the 15 states in terms of the Bayesian information criterion (BIC). Model sufficiency was also confirmed using the Kolmogorov-Smirnov (K-S) test and the Ljung-Box test.

[4]Farmland return to farmers who derive income from farming might be different from the return to investors who collect cash rents. However, empirical evidence (Du, Hennessy, and William, 2007) shows that the difference is rather small in the long-run.

[5]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

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