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Effects of interest rate changes on midwestern U.S. farmland values

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The student author, whose presentation of the scholarship herein was approved by the program of study committee, is solely responsible for the content of this thesis. The Graduate College will ensure this thesis is globally accessible and will not permit alterations after the degrees are conferred.

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DEDICATION

This journey would not have been possible without the love and support of my family. I dedicate this milestone to them because they never ceased to encourage me to follow my heart and explore new directions in life. I am forever indebted to **my parents**, Mumin and Afërdita, for their sacrifices because they gave me opportunities and helped shape me into the person I am today. To my **brother**, Gëzim: thank you for being one phone call away despite the 7-hour time zone difference and for helping me through my doubts. To my **best friend**, Klementina: I am grateful for your love and encouragement. Thank you for always magnifying my achievements no matter how small they were.

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ABSTRACT

The U.S. Department of Agriculture (USDA) estimated that over 83% of the 2018 farm sector's assets were held in real estate. In this study, the effects of recent interest rate hikes on Midwestern farmland values were quantified by developing three first-order autoregressive distributed lag models using annual, inflation-adjusted, state-level farmland value and gross farm income data and real federal funds rate levels. The model estimations used observations from 1963 to 2015 and were evaluated with out-of-sample forecasts for 2016 and 2017. Results were robust with Arellano-Bond estimation and an error correction model. A one-percentage point increase in the federal funds rate induced an immediate decrease in farmland values of nearly 1%. Immediate effects were small in magnitude; however, median lag length calculations indicated that long-term impacts of changes in interest rates are much larger. In the long-run, a one-percentage point increase in the federal funds rate generates an overall decrease in farmland values of 25% in the I-states (IL, IN, IA) and Lakes (OH, MI, MN, WI) regions, and a decrease of 43% in the Great Plains (MO, KS, NE, ND, SD) region. Results indicate that it takes six, nine, and eleven lags for half of the farmland value decrease to occur in the I-States, Lakes, and Great Plains, respectively. The substantial long-term effects of interest rate hikes and the projected future increases of the federal funds rate indicate that this study has direct implications on monetary policy, especially considering the growing farm financial stresses resulting from farm income declines.

CHAPTER 1. GENERAL INTRODUCTION

Farmland constitutes one of the most important agricultural assets in the United States – it represents over 83% of farm assets (U.S. Department of Agriculture, 2018). Historically, the prices of farmland have followed "booms" and "busts;" with a swift and substantial decline occurring during and after the 1980s farm crisis. Given that farmland is a major agricultural asset, researchers have developed models with various different factors that may be used to explain variations in farmland values across time. Previous research indicated that important factors which impact variation in farmland values include capitalization rates (Burt, 1986; Featherstone & Baker, 1987; Moss, 1997; Ricardo, 1817; Sherrick, 2018; Zhang & Tidgren, 2018), farm income – net and gross (Featherstone, Taylor, & Gibson, 2017; Renshaw, 1957; Reynolds & Timmons, 1969; Walker, 1976), government programs and payments (Barnard, Whittaker, Westenbarger, & Ahearn, 1997; Featherstone & Baker, 1988; Klinefelter, 1973; Shaik, Helmers, & Atwood, 2005) , inflation rates (Just & Miranowski, 1993; Moss, 1997), and other non-economic factors such as population growth and/or soil characteristics (Drescher, Henderson, & McNamara, 2001; Miranowski & Hammes, 1984).

During the past few months, the Federal Reserve announced that it plans to increase the federal funds rate from historic lows of the past decade; such interest rate increases are expected to impact farmland values. This study quantified the effects of rising interest rates on Midwestern farmland values.

Three first-order autoregressive distributed lag (ARDL) models were developed by using annual state-level data for inflation-adjusted farmland values, gross farm income, and real interest rates for three important agricultural regions in the United States – the I-States (Illinois, Indiana, Iowa), the Lakes (Ohio, Michigan, Minnesota, Wisconsin), and the Great Plains (Missouri, Kansas, Nebraska, North Dakota, South Dakota). Unlike recent previous research (Featherstone et al., 2017), our models serve as regional-based instruments (considering more than one individual state) that explained at least 99.4% of the variation in farmland values in those 12 agricultural states. Additionally, the predictive power of our models was tested with out-of-sample forecasting, as opposed to within-sample-estimation (which historically was the main method in the literature). Our model was run using observations from 1963 to 2015, and farmland values for 2016 and 2017 were predicted using the model estimates.

The main specification of our models included only inflation-adjusted gross farm income and real interest rates as regressors; however, we also tested other factors (as suggested by the published literature) such as government direct payments, conservation reserve program (CRP) payments (which require dropping pre-1986 observations given that CRP payments are relatively recent), and livestock income. These variables, however, were dropped from the models due to multicollinearity issues that affected the estimated coefficients, fit of the estimated model, and both direction and magnitude of the effects.

CHAPTER 2. REVIEW OF LITERATURE

Agricultural land accounts for over 83% of all farm assets, and there has been extensive research interest in mapping important factors that explain fluctuations in farmland values (Burns, Key, Tulman, Borchers, & Weber, 2018). In the United States, farmland has experienced “boom” and “bust” cycles that have spurred intense interest among researchers to understand the main factors driving these cyclical differences and to derive empirical farmland value models.

General Factors Influencing Farmland Values in the United States

Historically, farmland has been used extensively for the production of food and fiber; however, as non-agricultural demand to use land for non-agricultural purposes has greatly expanded, it affected the value that farmers received for this atypical production good. The primary historical uses of farmland explain why economists believed that farmland values were directly tied to farm income and, therefore, why examining one would explain variations in the other (Reynolds & Timmons, 1969). Nevertheless, increases in demand for land use purposes other than farming (e.g., business expansions, housing) induced a divergence of farmland values from farm income and drove economists to address the issue from other angles (Chryst, 1965).

Farm income

The farm income approach was likely the first approach used to appraise farmland values in the United States (Walker, 1976). It was expected that the stream of income received from the land would be a reasonable and accurate measure of land values; after all, income received from farmland is a numerical version of the land’s productivity. However, farm income has not followed the exponential increases seen in farmland values (Tables 1 and 2).

Table 1. Gross and net farm income, and farmland value in the U.S., 1960-2017 (USDA)

	1960	1970	1980	1990	2000	2010	2017
A) Gross Farm Income (In Billions $)	256	300	390	343	342	392	440
B) Net Farm Income (In Billions $)	74	73	42	80	72	89	77
C) Farmland Value (In $/Acre)	117	196	737	683	1090	2150	3080

Table 2. Ratios of gross and net farm income to land values in the U.S., 1960-2017 (USDA)

	1960	1970	1980	1990	2000	2010	2017
Ratio: Gross Farm Income To Farmland Value	2.19	1.53	0.53	0.50	0.31	0.18	0.14
Ratio: Net Farm Income To Farmland Value	0.63	0.37	0.06	0.12	0.07	0.04	0.03

Ratios of gross and net farm incomes to farmland values in the U.S. have decreased over time due to the increases in farmland values being larger than the increases in farm incomes. For example, farmland values increased by 43.3% from 2010 to 2017, but gross farm income increased by only 12.2% and net farm income actually decreased by 13.4% (U.S. Department of Agriculture, National Agricultural Statistics Service, 2018a).

Over the past few decades researchers have studied the impact of net farm income on farmland values empirically and have provided valuable inference on this impact. Renshaw (1957) found that inclusion of the “weighted average of past income rather than last year’s income alone” (Renshaw, 1957, p. 507) increased the explanatory power of the farmland valuation model (R-squared in his 1920-1953 model went from 0.72 to 0.79); therefore, he argued that the land market ought to include past returns from more than one year (Renshaw, 1957). A cross-sectional analysis of the effect of net farm income on farmland values was performed by William H. Scofield in 1964 (as cited by Reynolds & Timmons, 1969, p. 329), and analysis revealed that between 83 to 89 percent of the variation in farmland values across the United States was explained by net farm income. Scofield's analysis was performed with data from three different time periods: 1936-1940, 1951-1953, and 1961-1963 (Reynolds & Timmons, 1969, p. 329). Strohbehn (1966) found evidence that farm income had been capitalized over time into land value; therefore, by 1959, land prices had been elevated to exceed land productivity value (Strohbehn, 1966). This indicates the importance of farm income to explain farmland values.

Recent research investigating the relationship between farmland value and farm income on farms in Kansas was conducted by Featherstone, Taylor, and Gibson (2017). The farmland value model used for analysis was:

$$\mathrm{L_t} = \alpha_t + \alpha_2 \mathrm{I_t} + \mathrm{t_1 L_{t-1}} + \mathrm{t_2 L_{t-2}} \tag{1}$$

where, $\mathrm{L_t}$ is value of land at time t, and $\mathrm{I_t}$ is the net farm income at time t, $\mathrm{L_{t-1}}$ is the value of land lagged by one period, and $\mathrm{L_{t-2}}$ is the value of land lagged by two periods (Featherstone et al., 2017, p. 145). Findings suggested that increases in net farm income in Kansas drove farmland values higher (at 90% or better confidence level) for seven of Kansas' crop reporting districts after being corrected for first-order autocorrelation (Featherstone et al., 2017). In addition, changes in net farm income induced adjustments of land values "slowly with a one-year elasticity at the state level of 6.7 percent" (p. 150). These findings indicated that farm income is important in explaining farmland values.

Governmental farm programs and payments

The relationship between farmland values and governmental farm programs and payments was studied by various researchers, and it was hypothesized that this relationship was positive due to capitalized benefits of these programs into farmland values (Klinefelter, 1973). It is reasonable to assume that government programs, having been in existence for decades, have enabled farmers to receive higher net returns (Kirwan, 2009); additionally, these higher net returns must capitalize into higher farmland values. Government programs tailored toward land diversion and land use restrictions may impact farmland values in two important ways: (1) acre diversion and land use restriction may generate competition among farmers in buying land - driving prices up; and (2) price-support programs may provide security against income fluctuations and thus increase net returns to land (Klinefelter, 1973, p. 28; Reinsel & Reinsel, 1979).

Featherstone and Baker (1988) analyzed the effects of U.S. agricultural market movement towards a free market economy and away from the 1985 governmental farm programs on Midwestern farmland prices (Featherstone & Baker, 1988). The primary finding of their research was that farmland prices and cash rents typically would be 13% lower and less variable under free market conditions compared with those under the 1985 farm programs (Featherstone & Baker, 1988, p. 188). Simulation results for land price (1987-1990) under both the free market and 1985 farm programs scenarios showed that the lowest land value under the 1985 programs scenario would be $1048/acre in 1987 whereas under the free market scenario would be $657/acre in 1990. Similarly, the highest land value under the 1985 farm programs and free market scenarios would be $1793/acre and $1814/acre, respectively, in 1990 (Featherstone & Baker, 1988, p. 186). These results supported the expectation that there is higher risk associated under the free market scenario.

More recent research indicated that despite the accrued benefits from government farm program payments, farmers also incur opportunity costs when enrolling in those programs, namely foregone revenue for the acres of land they choose to idle from production (Barnard et al., 1997). In two different regression-based analyses (ordinary least squares and non-parametric estimation), Barnard et al. (1997) studied the effects that government payments had on cropland values in twenty United States Land Resource Regions (LRR). They found that government payments were consistently significant (99% level of confidence), and the impact was positive as expected. In addition, they also found that removing government payments from these regions would lead to reductions in farmland values ranging from 12 to 69% (equivalent to reductions in value of $104 to $903 per acre) (Barnard et al., 1997, p. 1647).

Similar results were obtained by Shaik, Helmers, and Atwood (2005) who developed an extended version of the basic capitalization model (Burt, 1986) to estimate the relationship between cropland values and government programs in forty-eight U.S. states for the time period 1940-2002. Government programs had a significant, positive relationship with cropland values; as much as a 30 to 40% increase in cropland values during 1938-1980, but only a 15 to 20% increase since 1980 (Shaik et al., 2005, p. 1197). In another study, government payments accounted for 21.2% of net farm income in the Southern Plains states of the United States; Delta states and Corn Belt states appeared to be even more sensitive (Moss, 1997). Reductions of government payments indirectly affected farmland prices through their direct effects on farm income. It was concluded that removing government payments led to a large reduction in net farm income and that returns on agricultural assets were more important in explaining farmland variations in regions which relied heavily on government payments as a large percentage of net farm income (Moss, 1997).

Another indirect, but important, effect of government programs on farmland values is through increases in average farm size (Klinefelter, 1973). Government programs tied to acreage diversion increased burden on fixed resources (capital, labor) to compete for additional land in order to spread such fixed costs, and thus farmland prices increased (Klinefelter, 1973). Additionally, government price support programs which are coupled with advances in technology have led to increased incentives to obtain additional land to allow for technological gain acquisitions (Klinefelter, 1973). As evident by research results, government payments and programs play an important explanatory role in farmland valuation models.

Farmland size and transfer of ownership

There has been widespread interest in understanding the impact of the size of farms and the number of voluntary ownership transfers on farmland value.

Technological advancement (i.e., larger machineries) have played a direct role in increasing demand for land. Advanced technologies used in the field allow farmers to manage larger acreages, increasing motivation to increase farm size and hence increasing farmland prices (Reynolds & Timmons, 1969). Additionally, the concept of "economies-of-scale" applies in this case because the farmer can spread operating costs across a larger number of acres, thereby decreasing unit costs of production and increasing income as a result (Klinefelter, 1973; Reynolds & Timmons, 1969). Reynolds and Timmons (1969) reported that farmland size was significant in explaining farmland prices, and its effect on farmland value was positive (p. 341).

Farmland ownership transfers are also important in explaining variation in land prices. Klinefelter (1973) and Reynolds and Timmons (1969) defined ownership transfers to include voluntary sales of farmland, inheritances, foreclosures and transfers resulting from other circumstances as long as the condition of an open market situation between buyers and sellers was maintained. In the United States, there is a strong trend for farms to increase in size (average farm size in 2009 was 423 acres and 444 acres in 2017 - an increase of nearly 5%). However, the number of U.S. farms is concurrently decreasing annually (2.17 million farms in 2009 and 2.05 million in 2017 - a nearly 6% decline) (U.S. Department of Agriculture, National Agricultural Statistics Service, 2018b). Therefore, there is ample evidence to suggest that the strong demand for increasing farm size, economic factors (i.e., farm-level cost per unit of production), and declining numbers of farms transferred across the United States result in intense competition to acquire farmland; this higher demand for land translates into higher prices (Klinefelter, 1973; Reynolds & Timmons, 1969).

It was implicitly assumed that transfers of farmland would have a negative effect on farmland prices (Klinefelter, 1973; Reynolds & Timmons, 1969). Analysis performed by Reynolds & Timmons (1969) revealed that voluntary farmland transfers significantly reduced farmland values, and the same result was reported by Klinefelter (1973).

Inflation rate

Inflation is a natural phenomenon in any economy. Although the United States' economy experienced stable inflation rates during the past decade, that has not been the case historically. Given that land values are expressed in dollar amounts, Klinefelter (1973) claimed that land values are "embodied in the dollar value of the asset" (p. 27) and hence in the inflation rate. Inflation rates and farmland values are positively correlated (Klinefelter, 1973; Sherrick, 2018).

There are two implications of farmland values when accounting for inflation: (1) inflation decreases the capitalization rate of future returns on land; and (2) land "serves as a hedge against inflation" (Just & Miranowski, 1993, p. 157). If the only direct effect of inflation is changes in the discount rate, then inflation is believed to decrease farmland values; however, if the effect of inflation manifests itself as increases in food prices (which consequently raises net farm incomes), then inflation is believed to increase farmland values (Huang, Miller, Sherrick, & Gómez, 2006).

Just and Miranowski (1993) estimated a "nonlinear seemingly unrelated regression (SUR)" model utilizing state-based, cross-sectional, time-series data from 1963 to 1986 (p. 164). Results were reported for Iowa (Corn Belt representative state), Kansas (Wheat Belt representative state), Georgia (Southeast representative state), and the United States with R-square values of 0.915, 0.957, 0.947, and 0.947, respectively (Just & Miranowski, 1993). Among other important and statistically significant variables, inflation alone explained 25% of the predicted increase in prices in 1973 and 15% of the predicted price increases in 1974 in the state of Iowa (p. 166).

Moss (1997) studied the valuation of farmland for the 1960-1994 period based on the explanatory power of interest rates, inflation, and return on agricultural assets as primary regressors. Moss (1997) performed both state and regional-level analyses, and results indicated that inflation explained the majority of the variation in farmland values in Florida and across the United States; however, interest rates appeared statistically more significant in explaining variation in the Northeast region of the United States (primarily driven by the Maryland farmland regression). State-level comparisons at the marginal level show that median contribution of inflation to explaining farmland values was 82.66%, and it ranged from 6.33% to 98.13% across the states (Moss, 1997, p. 1314). Therefore, undoubtedly, inflation is considered an important variable to explain farmland values.

Non-economic factors: rising population pressures and soil quality

Additional important factors worth addressing when modeling farmland values extend outside traditional economic perspectives. One important factor is the pressure created on farmland values from human population increases. As population increases, there will be both increased demand for food (which often “requires” expansion of farmland) and increased demand for land use for residential or business purposes (Reynolds & Timmons, 1969). This latter phenomenon is often referred to as “urban sprawl”. Population growth, which increases demand for land regardless the purpose, is also expected to drive land prices higher (Drescher, Henderson, & McNamara, 2001; Shi, Phipps, & Colyer, 1997).

Soil characteristics (i.e., topsoil depth, pH, erosivity) constitute another factor whose effects on farmland values have been examined. Topsoil depth and soil pH levels had a positive effect on Iowa farmland values; however, erosivity (as expected) had a negative effect (Miranowski & Hammes, 1984). The marginal increased value of an additional inch of topsoil ranged from $12 - $31/acre, whereas a one ton/acre reduction in erosion potential led to a marginal increase of about $5.60/acre (Miranowski & Hammes, 1984, p. 748)

Using Interest Rates to Explain Farmland Values

Interest rates play a pivotal role in helping explain variations in asset prices because the valuation of land can be considered similar to valuation of other assets that generate a stream of present and future income (Harris, 1979). As such, land value is represented as “the net present value of all discounted future income flows [Ricardo, 1817]” (Zhang & Tidgren, 2018). Lower interest rates are favorable for farmland values for two important reasons: (1) they increase the demand for farm loans because of lower payments of interest; and (2) they indicate less attractive returns on competing assets of farmland (e.g., stocks and bonds) thereby increasing demand for land (Zhang & Tidgren, 2018). Zhang and Tidgren (2018) also discussed the importance of interest rates in agricultural production debt and capital by referencing the unusually high interest rate of the 1980s which led to high farm loan payments and subsequently to the U.S. farm crisis. The relationship between interest rates and farmland values is hypothesized to be negative (Burt, 1986; Featherstone & Baker, 1987; Sherrick, 2018); however, there has been instances that results have indicated a positive relationship (Shi, Phipps, & Colyer, 1997) which was argued to have been driven by the fact that interest rates served as a proxy for inflation.

In the United States and other developed economies, interest rates remain at low levels (stable at slightly below 2%) since the global financial crisis of 2008. This stability was induced mainly by premium increases of international investments to ensure liquidity of assets and by lower global economic growth (Negro, Giannone, Giannoni, & Tambalotti, 2018). However, the Federal Reserve has recently increased the federal funds rate, and it has announced further increases in the future (Figure 1).

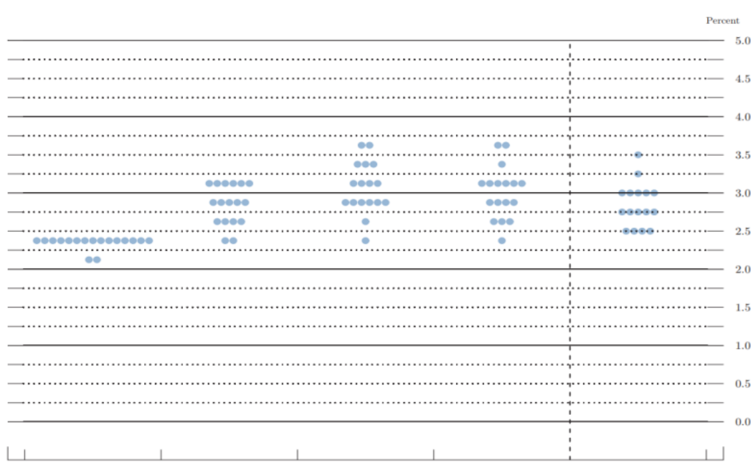

Figure 1. Midpoint of target level and range for the federal funds rate (Federal Reserve, 2018)

Sherrick (2018) argued that farmland values should behave similarly to other income-generating assets, and he used the theoretical, basic capitalization model where farmland is modeled as an indefinite earning-income asset (R) at time t :

$$\text{Farmland value}_t = \text{Expectation}_t\left[\sum_{i=1}^{\infty}\frac{R_t + i}{(1+r)^i}\right] \tag{2}$$

The model is then transformed into the form below (Sherrick, 2018) after accounting for a constant discount rate (r) and future income growth (g):

$$\text{Farmland value}_t = R_t\left[\frac{1}{r-g}\right] \tag{3}$$

Some noticeable expectations when using this model are: (a) higher (lower) future returns imply higher (lower) farmland values; and hence (b) increases (decreases) in interest rates decrease (increase) farmland values given that future incomes are discounted to today's dollars (Sherrick, 2018).

In Figure 2, agricultural land values are plotted against the 10-year U.S. treasury constant maturity rates (CMT-10) for the time period 1962 to 2016. CMT-10 was chosen because it represents a proxy for farmland capitalization rates (Sherrick, 2018).

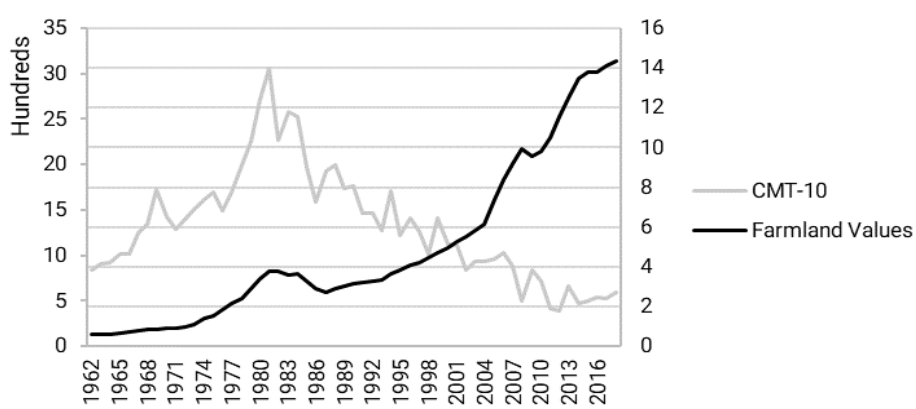

Figure 2. Farmland values plotted against CMT-10 (USDA, NASS; FRED)

Since the US farm crisis of the 1980's, farmland values were higher (lower) when treasury rates were lower (higher) – thereby demonstrating an inversely correlated relationship. In addition, it is widely accepted that low interest rates have contributed significantly to the resilience of farmland values despite divergence from lower farm income levels (Sherrick, 2018).

One report, however, claimed that the cost of capital (interest rates) explained more variation in farmland values when compared to returns on assets; however, interest rates explained less variation than did inflation (median contribution by inflation was approximately 83%, while only 8% for interest rates) (Moss, 1997).

Single-Equation Farmland Value Models

The basic model used in contemporary farmland valuation models and the model that enhanced the understanding of farmland prices and rents originated from David Ricardo's formulation of the theory of rent in his Principles of Political Economy and Taxation book (Ricardo, 1817). Ricardo's model is often referred to in the literature as the basic capitalization model (Nickerson & Zhang, 2014). A similar model was initially used by Burt (1986) to explain the behavior or the price of farmland which follows other income-generating assets following the capitalization formula. Burt's (1986) model, in equation (4), assumes constant capitalization rate r and fixed quantity of farmland entirely driven by prices and by demand-supply economics:

$$P_0=\sum_{t=1}^{\infty}\frac{R_t}{[(1+r_1)(1+r_2)\ldots(1+r_t)]}=\sum_{t=1}^{\infty}\frac{R_t}{(1+r)^t} \qquad (4)$$

where, R_t represents the rents obtained in year t, and r is the constant discount rate used to discount future rents received (Burt, 1986).

Burt (1986) argued that rents of farmland are influenced by numerous factors unable to be forecasted within farmland markets (Sherrick, 2018); therefore, some level of future expectation should be included in the model. As such, some concerns emerged with the very simple, constant discount rate assuming model in equation (4). It is questionable that the discount rate remains constant when modeling farmland values and rents; the discount rate is known to vary with economic and business cycles and expected inflation as has been the case historically in the United States (Burt, 1986). Subsequent research further tested the simple, present-value model of farmland prices empirically (Falk, 1991). Falk (1991) used 1921-1986 Iowa farmland value and rent data to test the present-value model used for farmland prices. He found that farmland values were highly correlated with rent prices; however, there was insufficient evidence to suggest that the movements of farmland prices were consistent with the implications generated by the present value model and that rent movements were less volatile than farmland prices (Falk, 1991). One potential explanation for this result, as provided by Falk (1991), was the tendency of Iowa farmland markets to act in a "myopic manner" (p. 8). By being nearsighted, Iowa traders ignore the tendency of downturns to be offset by future increases in value; hence, price of land is driven downward (Falk, 1991). In addition, it was evident that farmland values in Iowa were more likely to overreact to rent movements, i.e., changes of farmland prices were found to move more than proportionally with changes in rents (Falk, 1991).

Kleinfelter (1973) modeled Illinois farmland values across a 20-year time period (1951-1970) to better understand key variables that explain variations in those farmland values. Annual time-series data for Illinois farmland values were used, and an ordinary least squares regression model was run where four different equations were tested (Klinefelter, 1973). Klinefelter (1973) identified seven potential factors that were tested for relevance – inflation, government payments, expected rents, farm enlargements, farm transfers, capital gains, and technological advances (Klinefelter, 1973).

The first regression equation included all seven variables in the model; however, the results were deemed unreliable due to high evidence of multicollinearity that led to the signs of coefficients not appearing as expected and as suggested by economic theory, despite high explanatory power (R-square of 0.99) (Klinefelter, 1973, p. 30). Similarly, the second model also had multicollinearity issues despite some variables being deflated (government programs, expected capital gains, and previous three-year moving average net rents) and another one (previous three-year moving average corn yield) was dropped. The second model explained 97.9% of the variation in Illinois farmland values, but the government payments variable did not have the expected sign - most likely due to high correlation between farm size and value of government payments. In equation three, the government payments variable was dropped, and the new equation had an R-square of 0.973 and all explanatory variables had the signs that were suggested by theory (p. 31). Another model (equation four) was developed to help generate coefficient elasticities and to test for linear equation fit. In this model, the variables were transformed in logarithms (Klinefelter, 1973).

Results indicated that the linear model was accurate and that four explanatory variables (net rent, farm size, farm transfer, and expected capital gains) were significant in explaining 97.3% of the variation in Illinois farmland values (Kleinefelter, 1973). It was also concluded that, although government payments and previous three-year moving average of corn yields were dropped from the model, their importance remained in the model because they were reflected in farm size and net rent (Klinefelter, 1973). One limitation that Kleinefelter (1973) identified in the model was omitting interest rate as a potential explanatory variable; it was suggested that future research focus on the potential usefulness of interest rates in explaining farmland values.

Multiple-Equation Farmland Value Models

Contrary to the simple equation farmland modeling and to controlling for the associated disturbance/error terms when assuming a constant capitalization rate *r*, researchers focused on explaining farmland values by using a simultaneous, multiple-equation modeling framework. The most famous models include those of Herdt and Cochrane (1966), Tweeten and Martin (1966), and Reynolds and Timmons (1969).

Herdt and Cochrane (1966) analyzed the demand-supply forces of farmland markets to explain variation in U.S. farmland prices after 1951. They utilized the theory of the firm and the concept of economies of scale under a technological advance assumption to describe factors driven by demand. Advances in technology, they argued, may decrease costs per unit of production and subsequently induce a lower marginal cost for the farmer and hence an incentive to expand operations/buy more land. The expectation of higher income resulting from technological changes within farms would lead to continuous attempts to purchase land, thereby increasing land prices by the law of demand (Herdt & Cochrane, 1966). Expansion of operations and output was sustained by price-support mechanisms for farms which allowed prices to remain not only stable but also resistant to downward pressure due to the inelastic demand for agricultural products; hence, income remained intact (Herdt & Cochrane, 1966).

On the supply side, Herdt and Cochrane (1966) enlisted potential non-price factors (e.g., off-farm employment income & returns on non-farm investments) to explain why the supply for land would shift (keeping in mind that total land area of the United States is fixed, but total acreage of farmland changes). The empirical model consisted of two simultaneous equations: 1) the demand relation equation expressed by price, interest rate, index of productivity, urban land, general price level, and ratio of indices of prices received by farmers to the one paid by farmers; and 2) the supply relation equation expressed by price, interest rate, unemployment rate, and quantity of land in farms (Herdt & Cochrane, 1966). The model indicated that interest rates (although with an unexpected coefficient sign), unemployment rates, quantity of land in farms, general price level, ratio of prices paid by farmers to prices received by farmers, and the productivity index of the land influenced farm supply and price of land strongly, whereas other factors had secondary importance in describing variation in land prices (Herdt & Cochrane, 1966). Herdt and Cochrane (1966) concluded that technological advances played an important role in driving farmland prices upward because of the expected higher income effect experienced by farmers and the concomitant attempt to purchase land to expand operations and capture higher incomes.

Tweeten and Martin (1966) were also among the earlier researchers to develop a model that would predict U.S. farmland price variations. Their econometric model used annual time-series data (1923–1963) by means of ordinary, autoregressive, and recursive least squares and explained farmland value increases since 1950. Tweeten and Martin (1966) did not agree that net income explained entirely the land price variations seen in the post-1950 years; therefore, they utilized five endogenous variables to construct their final model: 1) land price, 2) land in farms, 3) cropland, 4) number of farms, and 5) farm transfers (Tweeten & Martin, 1966).

The first equation – land price equation – addressed the primary concerns held by the authors, and the land price equation examined the following factors: current values of land price, quantity of land available, land transactions, and number of available farms (Tweeten & Martin, 1966). The other four equations (land in farms, cropland, farm numbers, and farm transfers) were used to identify indirect effects on land prices by the farmland market. The explanatory power of the land price model was significant (95% probability level). Quantity of land in farms, agricultural real estate transfers, and number of farms appeared to be negatively correlated with farm price, whereas increases in lagged net farm income induced increases in land prices (Tweeten & Martin, 1966). The independent variables (lagged net farm income, non-farm investment rate of return and land prices, along with number of farms, farm transfers, and number of land in farms) explained more than 90% of the variation in land prices in this model (Tweeten & Martin, 1966). These authors used their data and the five-equation model to support the hypothesis that farm consolidation pressures and capitalized benefits from the governmental programs explained the increase in U.S. land prices since the 1950s. Unfortunately, analysis with more recent data (1946-1972) revealed a lack of statistical significance and extensive sign changes compared to original estimates (Pope, Kramer, Green, & Gardner, 1979). Such results implied that perhaps the methodology used by Tweeten and Martin (1966) is not applicable to other time periods despite passing robustness checks when the model was developed.

Reynolds and Timmons (1969) generated the third rendition of the well-known simultaneous-equation farmland price models. Their goal was to identify and quantify relevant variables that influenced farmland values. In order to do so, they developed a two-equation recursive model of the farmland market and used deflated aggregate U.S. farmland time-series data from 1933 to 1965 (Reynolds & Timmons, 1969). Findings indicated that voluntary farmland transfers, land diversity and conservation government payments, expected net farm income and capital gains, farm expansion, and the inverse of rate of return on stock accounted for most of the variation in farmland values (Reynolds & Timmons, 1969). It appeared that government payments tailored to land diversion had a stronger positive impact on farmland values than conservation payments; likewise, the debt-to-equity ratio affected farmland values more than the ratio of expected farm to non-farm earnings (Reynolds & Timmons, 1969). Cross-sectional analysis (additional analysis to deal with autocorrelation and multicollinearity within the data) indicated that expected net farm income, capital gains, and non-farm population density had a positive effect on land values; farm enlargement had a larger impact on value of farmland without buildings (more expansion possibility) than in farmland with buildings (Reynolds & Timmons, 1969). Results also indicated the expected negative effects of interest rate and voluntary transfers of farmland on farmland values (Reynolds & Timmons, 1969). Unfortunately, when the same model was estimated with data in a more recent time period (1946-1972), half of the coefficients appeared with a reverse sign, only one coefficient was statistically significant, and there were numerous changes in the magnitude of the coefficients (Pope et al., 1979).

The Herdt and Cochrane (1966) model explained earlier, however, was chosen as an ideal simultaneous-equation farmland price model when compared with the models of Tweeten and Martin (1966) and Reynolds and Timmons (1969) because it had the least number of sign changes when compared with original parameters and results, and it did not include lagged variables (Pope et al., 1979). The model was employed to analyze more recent data and to compare with estimated models similar to the Klinefelter (1973) single-equation model (which was chosen due to high explanatory power; R^2 in the 1913-72 model was 95.2% and in the 1946-72 model was 98.9%) with the goal of elucidating which models best explain variations in farmland values (Pope et al., 1979). The single-equation model performed better in within-sample (only the 1946-1972 model) and out-of-sample forecasts (both single-equation models) than the Herdt and Cochrane (1966) multiple-equation model. With the 1946-72 modified Klinefelter model, the within-sample root mean square error (RMSE) was 4.73 and lowest when compared to the rest of the models used; with both 1913-1972 and 1946-72 models, the out-of-sample RMSE was 44.49 and 40.35, respectively, and lower than all versions of

Herdt and Cochrane (1966) (Pope et al., 1979, p. 111). These findings indicated that the simple equation models can forecast better than previously believed.

Empirical Methods and Challenges to Modeling Farmland Values

Common and widely accepted models to evaluate variations in farmland values include time-series and cross-sectional models with aggregate data, distributed lag models, vector autoregressive models, and hedonic models (Nickerson & Zhang, 2014).

Time-series and cross-sectional data are commonly used to model farmland values. This dynamic approach involves use of aggregated data, given that high quality disaggregated farmland data may not be available (Zhang & Tidgren, 2018) In-depth investigations into time-series modeling of farmland values, however, indicated that there is violation of assumptions that may lead to unreliable results. Stationarity is assumed in time-series models; however, asset prices exhibit non-stationary characteristics. Present-value models were tested for stock and bond markets, and the present-value model for stock data was deemed unsuitable (Campbell & Shiller, 1987).

A distributed-lag model is a dynamic model where the effect of one explanatory variable x on the variable of interest y occurs over years (as opposed to one point in time). Distributed-lag models are relevant for modeling farmland values because these models place a stronger emphasis on recent (although past) returns on farmland given that future expected returns cannot be observed (Nickerson & Zhang, 2014). One disadvantage to using distributed-lag models is the incidence of multicollinearity. Multicollinearity appears when one of the regressors (say $\mathrm{X_t}$) is highly correlated with another regressor/s used to represent the lags (for instance, $\mathrm{X_{t-1}}, \mathrm{X_{t-2}}$). In this case, coefficient results will be biased because of the high correlation between independent variables; the coefficients will also have large standard errors (Gasparrini, Armstrong, & Kenward, 2010). Alston (1986) investigated a distributed-lag model of farmland values by the expected benefits of owning land in time *(t+n),* discount rate, and opportunity costs of owning land. While more common distributed-lag models involve *(t-n)* variables or lagged values, Alston's model integrated future expectations of net benefits:

$$V_t = \int_0^{\infty} B^*_{t+n} e^{-\rho n} dn \tag{5}$$

where, V represents present value of land prices in time *t*, B^*_{t+n} is the expected net benefits in time ($t+n$) (n being the periods in the future), and ρ is the discount rate (Alston, 1986). Inflation had little (potentially negligible) effect on real farmland prices in the United States; however, most of the real growth in land prices was accounted by increases in net rental income between 1960 and 1980 (Alston, 1986). Burt (1986) also performed a second-order rational distributed lag on the net rents (R_t) from crop-share received by landowners in order to explain variation of farmland prices (P_t). Burt's model specified the dynamic regression equation as (Burt, 1986):

$$P_t = \left(\alpha R_t^{\beta_0} R_{t-1}^{\beta_1} R_{t-2}^{\beta_2} \dots\right) u_t \tag{6}$$

which was transformed into the equation (7) when logarithmic transformations were applied and linear homogeneity constraint was enforced (Burt, 1986):

$$\log P_t = \log\alpha + \frac{(\gamma_0 + \gamma_1 L)(\log R_t)}{(1 - \lambda_1 L - \lambda_2 L^2)} + \log\mu_t \tag{7}$$

In this formula, L represents the lag operator defined as $L^{j}_{Z_t} = z_{t-j}$ and R_t denotes fixed net rents (Burt, 1986).

Vector autoregressive models (VAR) are additional empirical methods that have been investigated when modeling farmland values. A vector autoregressive technique is useful to capture interdependencies among multiple time-series processes by generating and defining an equation for every variable based on own-value lags and other-variable lags (Nickerson & Zhang, 2014). Therefore, such econometric models account for correlations between neighboring observations in a time series (Mendehall & Reinmuth, 1978). Common vector autoregressive models have the following form (Mendehall & Reinmuth, 1978, p. 546):

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 Y_{t-2} + \cdots + \beta_n Y_{t-n} + \mu_t \tag{8}$$

where observations Y_{t-i} is the i-th lag of y. The general first-order autoregressive model (where only the first lag of the dependent variable is included) can expand to include n^{th}-order of autoregressive model, shown by equation (8) (Mendehall & Reinmuth, 1978). However, autoregressive models do not provide effective forecasts if the process being forecasted is unstable (Mendehall & Reinmuth, 1978).

To study the dynamic response of farm real assets to changes in interest rates and net returns, Featherstone and Baker (1987) utilized the vector autoregressive techniques to build a model which explained variations in U.S. land prices. The net returns and interest rate data used in the model dated back from 1910 to 1985 (p. 536). One through ten-order autoregressive models were tested, and the fifth-order model was chosen. The three-equation model was composed of real interest rates (*r*), real residual returns to assets (*R*), and real asset values (*A*) (p. 535-536):

1. $r_t = k_1 + a_1 t + \sum_{i=1}^{n} b_{1i} r_{t-i} + \sum_{i=1}^{n} c_{1i} R_{t-i} + \sum_{i=1}^{n} d_{1i} A_{t-i} + e_{1t}$ (9)

2. $R_t = k_2 + a_2 t + \sum_{i=1}^{n} b_{2i} r_{t-i} + \sum_{i=1}^{n} c_{2i} R_{t-i} + \sum_{i=1}^{n} d_{2i} A_{t-i} + e_{2t}$ (10)

3. $A_t = k_3 + a_3 t + \sum_{i=1}^{n} b_{3i} r_{t-i} + \sum_{i=1}^{n} c_{3i} R_{t-i} + \sum_{i=1}^{n} d_{3i} A_{t-i} + e_{3t}$ (11)

where t represents time expressed in years, n represents the number of lags, ($k, a, b, c,$ and d) are the parameters to be estimated by the model, and e_{it} represent the error terms for equation i (Featherstone & Baker, 1987). Results of the analysis revealed that: (1) real farm assets overreact to shocks in independent variables (interest rates, net returns, and asset values); however, the effect lasted up to six years, and (2) tendency for farm assets market to create bubbles (Featherstone & Baker, 1987).

Hedonic pricing models are additional important techniques to help generate farmland price models that depend entirely on attributes that characterize the land. In a seminal paper, the impacts of policy changes, local markets, environmental and agronomic drivers of productivity, and land use practices on the Irish agricultural land market were analyzed (O'Donoghue, Lopez, O'Neill, & Ryan, 2015). Data originated from the Irish National Farm Survey, and a random effects generalized least squares model was applied to the hedonic pricing model to understand the effects of the aforementioned characteristics on land values (O'Donoghue et al., 2015). Policy changes (i.e., direct payments per hectare) and agronomic characteristics (i.e. soil quality, rainfall, slope, temperature, wind speed, etc.) contributed to an increase in land values (O'Donoghue et al., 2015). In this model, 60% of the variation in farmland values was explained by the specified independent characteristics in the model; 20% of the price variability was explained by agronomic factors, 38% was explained by land market fluctuations, and farm practices in terms of land use and policy changes accounted for only 1% each (p. 13). Nevertheless, issues with spatial correlation were evident in this model, and such evidence was further supported by inconsistent signs of coefficients from one model to the other.

Ervin and Mill (1985) developed a farmland hedonic price model (for the time period 1976-1978 for Page County, Iowa) focusing primarily on incorporation of soil erosion effects on farmland values. Development of this model was driven by interest in control of soil erosion due to increased water pollution and increased agricultural exports in the 1970s driving demand for increased productivity. It should be noted that incorporation of such information into farmland markets will only occur if there is availability of such information (which will depend on the cost of acquiring such information) and if market failures arise. The acquisition of soil erosion information will be based on yield impacts and associated production costs (and not necessarily on water pollution effects) (Ervin & Mill, 1985).

Other hedonic models have been developed which examined impacts of various variables on farmland values [e.g., the impact of wildlife recreation income (Henderson & Moore, 2006); the impact of proximity to ethanol plants (Zhang, 2014); factors affecting agricultural land values in Kansas (Tsoodle, Golden, & Featherstone, 2006)]. Although hedonic models provide an opportunity to examine effects of land characteristics and attributes on farmland value, several potential concerns have been expressed regarding econometric problems with estimating unbiased effects when developing hedonic price models (Nickerson & Zhang, 2014).

Multicollinearity and autocorrelation

Multicollinearity exists when two or more independent variables in the model are correlated (Mendehall & Reinmuth, 1978). When developing models, the goal frequently is to make inferences regarding the effect of certain individual variables on the variable of interest. However, when independent variables are correlated, this causes concern because some estimated parameters may be underestimated while others may be overestimated) (Mendehall & Reinmuth, 1978). Multicollinearity also may cause particular variables to appear insignificant (significant) when they may be significant (insignificant) (Mendehall & Reinmuth, 1978). Multicollinearity can be detected easily by using variance inflation factors (VIF) which quantify the amount of variance that is inflated in the model. The undesirable effect of multicollinearity can be reduced by removing variables that possess high multicollinearity.

Autocorrelation, also referred to as serial correlation, occurs when the error terms in a regression are correlated (Halcoussis, 2004). Different from multicollinearity, however, autocorrelation in a multiple regression impacts the precision, but not the accuracy, of the estimated parameters (i.e., beta parameters are not biased, but their true variances are larger than actually estimated) (Mendehall & Reinmuth, 1978). Additionally, autocorrelation causes the errors to follow a pattern, which indicates that the model is missing important information and could perform better with the inclusion of unaccounted for variables; it also indicates that the sum of squares of residual error (SSE) is underestimated and that more unexplained variation is present than accounted for (Halcoussis, 2004; Mendehall & Reinmuth, 1978). The most common test for autocorrelation is the Durbin-Watson test, which tests only for first-order autocorrelation (i.e., errors correlated with errors that precede them immediately) (Halcoussis, 2004; Mendehall & Reinmuth, 1978). Autocorrelation can be addressed when utilizing methods other than ordinary least squares (OLS), when dealing with time series analyses (if data-based multicollinearity) or by altering the OLS model specification (if structural multicollinearity) (Halcoussis, 2004).

Sample selection and omitted variable bias

Sample selection bias occurs when “nonrandomly selected sample” are used “to estimate behavioral relationships” (Heckman, 1979, p. 153). It leads to inferences based on a sample that is not representative of the population being studied. Heckman (1979) argues that this sample selection bias may occur because of two reasons: 1) self-selection from data or individuals, and 2) selection decisions of researchers that mimic self-selection.

An applicable example to the farmland value topic is the fact that farmland rental rates can only be observed for land that is actually rented and that “unobserved factors determining inclusion in the subsample are correlated with unobservables influencing the variable of primary interest, leading to biased parameter estimates of the hedonic models” (Nickerson & Zhang, 2014). A Heckman-style selection model corrects for sample selection bias through estimation of a two-step procedure where inverse Mill’s ratios are formulated from the estimators of the selection equation (Heckman, 1979; Nickerson & Zhang, 2014). This model is widely applied in economics, especially in the context of farmland values research (Nickerson & Zhang, 2014).

Omitted variable bias, as the name suggests, occurs when relevant independent variables fail to be included in the model (Nickerson & Zhang, 2014). Omitted variable bias can be corrected with the use of instrumental-variable (IV) approaches. Kirwan (2009) utilized an IV approach to examine the proportion of the marginal subsidies acquired by owners of farmland by using farm-level data in the United States from 1992 to 1997. Results demonstrated that 75% of subsidies were absorbed by farmers and that only 25% of the subsidy actually went to the landowner; this was a contradiction of other prediction models (Kirwan, 2009). The IV approach allowed Kirwan (2009) to account for unobserved heterogeneity in the model, perhaps arising by farmer skill or soil quality (Kirwan, 2009). Controlling for omitted variable bias (unobserved heterogeneity), therefore, allows for better parameters that are not biased and for subsequent proper inference.

Broad Conclusions

From previous literature findings, it is evident that farmland prices are affected by numerous factors that can be grouped into economic conditions (e.g., interest rates, inflation, farm income), agro-environmental indicators (e.g., soil quality, pH level), and social issues (e.g., population growth, urbanization). Farmland comprises a highly important financial asset, and because future changes in policy (such as interest rate changes) will impact farmland values further study of this topic is warranted.

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CHAPTER 3.
THE IMPACT OF INTEREST RATE HIKES ON MIDWESTERN FARMLAND VALUES

Albulena Basha, Wendong Zhang, Chad E Hart

Abstract

The U.S. Department of Agriculture (USDA) estimated that over 83% of the 2018 farm sector's assets were held in real estate. In this study, the effects of recent interest rate hikes on Midwestern farmland values were quantified by developing three first-order autoregressive distributed lag models using real federal funds rate levels and annual, inflation-adjusted, state-level farmland value and gross farm income data. The model estimations used observations from 1963 to 2015 and were evaluated with out-of-sample forecasts for 2016 and 2017. Results were robust with Arellano-Bond estimation and an error correction model. A one-percentage point increase in the federal funds rate induced an immediate decrease in farmland values of nearly 1%. Immediate effects were small in magnitude; however, median lag length calculations indicated that long-term impacts of changes in interest rates are much larger. In the long-run, a one-percentage point increase in the federal funds rate generates an overall decrease in farmland values of 25% in the I-states (IL, IN, IA) and Lakes (OH, MI, MN, WI) regions, and a decrease of 43% in the Great Plains (MO, KS, NE, ND, SD) region. Results indicate that it takes six, nine, and eleven lags for half of the farmland value decrease to occur in the I-States, Lakes, and Great Plains, respectively. The substantial long-term effects of interest rate hikes and the projected future increases of the federal funds rate indicate that this study has direct implications on monetary policy, especially considering the growing farm financial stresses resulting from farm income declines.

Introduction

In 2018, agricultural land accounted for over 83% of all farm assets – 5.3 percentage points higher than in 1977 (U.S. Department of Agriculture, National Agricultural Statistics Service, 2018). For farmers, land represents an input for crop and livestock production as well as an income-generating asset that can be used as collateral to acquire operating or investment loans. Land constitutes the overwhelming majority of farm assets, and, therefore, it is also considered the most important asset in landowners' overall investment portfolios. To agricultural lenders, farmland serves as robust collateral on which lending decisions are made. Because farmland is an input for food production, farmland values influence commodity prices and consumer prices. Given that farmland is a critical asset in the agricultural economy that affects multiple parties, its values are important indicators of agricultural economy health.

This paper quantified the effects of rising interest rates on Midwestern farmland values. We constructed three first-order autoregressive distributed lag (ARDL) models using annual, state-level data for farmland values and gross farm income in twelve Midwestern states, and interest rate data. The predictive power of the models was tested with out-of-sample forecasting.

The contributions of this paper to the existing body of literature are two-fold: (*a*) the model was selected via out-of-sample validation as opposed to within-sample estimation, and (*b*) quantifying the effects of rising interest rates on farmland values (a non-methodological contribution).

General Factors Influencing Farmland Values

Historically, farmland has been used extensively for the production of food and fiber; however, as non-agricultural demand for land increased, it affected the value that farmers received for this atypical production good. The primary historical uses of farmland explain why economists believed that farmland values were directly tied to farm income and, therefore, why examining one would explain variations in the other (Reynolds & Timmons, 1969). Nevertheless, increases in demand for land use purposes other than farming (e.g., business expansions, housing) induced a divergence of farmland values from farm income and drove economists to address the issue from other angles, not just farm income (Chryst, 1965).

Researchers explained farmland value variations by using a wide array of explanatory variables. Although farm income did not follow an increasing trend as farmland values did, it still served as an important factor to explain variations in farmland values; it was one of the earliest approaches used to appraise farmland values (Strohbehn, 1966; Walker, 1976). Because farm income historically represented the stream of income received from farmland, it was considered a reasonable measure of farmland value (i.e., a numerical version of the land's productivity). Researchers who studied the effects of farm income on farmland values found that farm income explained almost 90% of the variation in farmland values across the United States (Scofield [1964] as cited by Reynolds & Timmons [1969]); furthermore, incorporating lagged farm income into farmland models increased explanatory power by 5% (Renshaw, 1957). Recent research in Kansas found that changes in net farm income adjusted farmland values positively but the adjustment was induced with a 6.7% one-year elasticity at the state level (Featherstone, Taylor, & Gibson, 2017).

Government payments and programs have also been considered important in explaining agricultural land values. Government programs may integrate into land values through two different avenues: (*a*) acreage diversion or land restrictions, and (*b*) price-support programs. Some researchers indicated that benefits (typically dollar subsidies) stemming from government programs will be capitalized into farmland values (Featherstone & Baker, 1988; Klinefelter, 1973); however, other researchers claimed that there are costs to farmers (namely foregone revenue) who enroll in government programs because land is taken out of production (Barnard, Whittaker, Westenbarger, & Ahearn, 1997). The increases in income received by farmers after enrolling in government programs and the indirect pressure to increase farm size (Klinefelter, 1973) directly impacted farmland values and served as insurance against fluctuations in commodity prices (Klinefelter, 1973; Reinsel & Reinsel, 1979). For example, the 1985 government farm programs allowed for 13% higher and more variable cash rents and farmland prices (Featherstone & Baker, 1988). A study performed in 20 U.S. Land Resource Regions (LRR) indicated that removal of government programs led to a 12-69% decline in farmland values subject to location (Barnard et al., 1997). Recent research done on 48 U.S. states from 1940 to 2002 further supported earlier findings by estimating as much as a 30-40% increase in land values from 1938 to 1980 was induced by government programs; however, programs led to only a 15-20% increase in 1980 farmland values (Shaik, Helmers, & Atwood, 2005).

Agricultural land values are affected by inflation rates, as are values of other income-generating assets. Klinefelter (1973) and Sherrick (2018) suggested that inflation rates and farmland values are positively related – the dollar value of farmland will always be higher when affected by inflation. Just and Miranowski (1993) argued that land serves as a hedge against inflation, and that inflation decreases the rate of capitalization. Inflation alone explained 25% of the 1973 increase in land prices and 15% of the 1974 land price increase. Inflation also explained the majority of variation in farmland values in Florida (Moss, 1997) and increased farmland values through surges in farm net income due to higher prices (Huang, Miller, Sherrick, & Gómez, 2006).

Interest rates, on the other hand, are inversely correlated with farmland values. At lower interest rates, demand for farm loans increases (due to lower interest payments) and signals lower returns on competing assets, thereby leading to a higher demand for land (Zhang & Tidgren, 2018). Interest rates explained more variation in farmland values than did returns on assets; however, they explained less than inflation (median contributions by inflation and interest rates are 83% and 8%, respectively) (Moss, 1997). It must be recognized, though, that interest rates are inherently incorporated into farmland value models, as they form the basis for capitalization models. Furthermore, it is argued that low interest rates are the primary driver of resilience for farmland values despite the divergence from farm income levels (Sherrick, 2018).

Two non-economic (yet important) factors that explain farmland value variations are pressures from an increasing human population and soil characteristics. Increases in human population have two implications for land prices: (*a*) more land is dedicated to residential uses (and, therefore, less for agricultural purposes); and (*b*) increased population leads to increased demand for food (and hence higher demand for the less-available farmland). Regardless of the driver behind the increased demand for land (residential, business, or farm-related reasons), a higher demand for land translates into higher land prices; therefore, the relationship between population growth and land value is positive (Drescher, Henderson, & McNamara, 2001; Reynolds & Timmons, 1969).

Soil characteristics are factors that have been overlooked by many studies when appraising farmland values; however, they are considered increasingly important because they dictate productivity of the land for farming purposes. Miranoswki and Hammes (1984) studied Iowa farmland characteristics (topsoil depth, pH, and erosion potential) and their relationship with farmland prices. Their results revealed that an additional inch of topsoil increased farmland prices by $12-$31/acre, whereas one-ton/acre decrease in erosion potential increased land values by $5.60/acre (Miranowski & Hammes, 1984, p. 748).

Most studies argue that farmland variations are methodologically studied by incorporating the basic capitalization formula (which accounts for the present value of cash rents) as was first introduced by the Ricardian theory of rents (Burt, 1986; Nickerson & Zhang, 2014; Sherrick, 2018). Other studies claim that a constant capitalization rate is not appropriate in an ever-changing economic world and that capitalization rates fluctuate and are subject to local, state, and national market trends (Herdt & Cochrane, 1966; Reynolds & Timmons, 1969; Tweeten & Martin, 1966). These latter studies integrated multiple-equation models into their analyses instead of relying simply on a single-equation basic capitalization model; they argue that simultaneous-equation models better explain variations in farmland values because they account for supply and demand forces across multiple dimensions. Nevertheless, the comparison of Klinefelter's (1973) single-equation model to Herdt and Cochrane's (1966) multiple-equation model using slightly more recent data showed that this single-equation model performed just as well and had a higher within-sample and out-of-sample forecasting power than did the multiple-equation model (Pope, Kramer, Green, & Gardner, 1979).

The evolution and determinants of farmland values have been extensively studied in agricultural finance and management literature, and such determinants include both economic and non-economic factors. However, at least two factors have generated significant renewed interest in the trajectory of farmland price movements: (*a*) recent interest rate hikes by the US Federal Reserve have resulted in the highest interest rate levels since 2008, and the Federal Reserve is expected to continue to increase interest rates in the years ahead; and (*b*) agricultural trade disputes with key trading partners have already led to lower commodity prices, which should negatively impact future farm income and, consequently, farmland values.

Common Econometric Methods to Estimate Farmland Values

Development of distributed lag and vector autoregressive (VAR) models (dynamic models), in addition to simple ordinary least squares and static methods, are common methodologies used to estimate factors that explain variations in farmland values. A distributed lag model is a dynamic model that takes into account long-term effects of explanatory variables on the variable of interest (as opposed to static models that focus only at time t). The distributed lag model methodology involves the addition of lagged independent variables in the model; however, doing so raises multicollinearity issues and may bias coefficients, increase standard errors, and indicate significance (insignificance) for variables that are otherwise insignificant (significant). Alternatively, VAR models can be used. These models are useful for capturing interdependencies among multiple time-series processes by generating and defining an equation for every variable based on own-value lags and other-variable lags (Nickerson & Zhang, 2014). This study utilized autoregressive distributed lag (ARDL) techniques, where lags of both dependent and independent variables are incorporated into the model.

Because time series data are often not stationary, the general ARDL models are transformed into error correction models (ECM) by means of first-order differencing (De Boef & Keele, 2008). The ECMs are developed on the basis of autoregressive distributed lags – the dependent variable is no longer the actual values of Y_t, but the difference in Y_t ($Y_t - Y_{t-1}$ or ΔY_t). This approach ensures stationarity and less biased coefficients. If the data are stationary when used to develop the ARDL model, the coefficients are consistent with those estimated by the ECM model (De Boef & Keele, 2008).

Generally, most of the models that estimate farmland values are predominantly developed with a specific goal – forecasting. Therefore, in order to evaluate forecasting power of farmland value models, genuine forecasts ought to be performed by using the model to forecast with new data (out-of-sample forecasting). This approach generates forecast errors, which are the differences between an observed value and its forecasted value, or $e_{t+k} = \hat{y}_{t+k|t}, - y_{t+k}$ (Mendehall & Reinmuth, 1978; Wooldridge, 2015).

Materials and Methods

Data for this study were obtained from three sources and consisted of annual, state-level data from 1962 to 2017 (inclusive). Data obtained for 12 states were grouped into three different regions: (*a*) I-States (Illinois, Iowa, Indiana), (*b*) Lakes states (Ohio, Michigan, Minnesota, and Wisconsin), and (*c*) Great Plains states (Missouri, Kansas, Nebraska, North Dakota, and South Dakota). Farmland value data were derived from USDA's National Agricultural Statistics Service (NASS). Gross farm income data were obtained from USDA's Economic Research Service (ERS). Federal funds rate data were obtained from the St. Louis Federal Reserve Economic Data (St. Louis FRED).

For each of the three regions, an ARDL model was developed that included one lag of the dependent variable (inflation-adjusted farmland value), two independent variables (inflation-adjusted gross farm income and real interest rate), and one lag of each of the independent variables. Serial correlation was addressed by adding the lag of the dependent variable (Featherstone et al., 2017), and robust standard errors were estimated to control for heteroscedasticity of the error terms. The model controlled for a linear trend and fixed effects to account for unobserved heterogeneity within the groups. Farmland values and gross farm income data were log-transformed to smoothen variability and transform skewed data into a normal distribution. Additional orders of lags were tested; however, both the Akaike information criterion (AIC) and Bayesian information criterion (BIC) tests indicated a first-order lag model was more appropriate for this dataset. Additionally, the Hausman test suggested that the fixed effects model is more appropriate for this dataset than the random effects model.

The first-order ARDL (1,1;2) model was run on the 1963-2015 timeline (1962 observations were removed given that lagged dependent and independent variables were used in the model; 2016-2017 data were used only to test prediction power of the model, not to estimate). The accuracy of explained variation in land values was estimated in two ways: (*a*) within-sample estimation, where predicted land values were compared with actual values for 1963 – 2015; and (*b*) out-of-sample forecasting, where the model was used to predict land values for 2016 and 2017.

Additional factors such as government direct payments, CRP payments, and livestock income were tested; however, these variables were dropped from the final model due to multicollinearity concerns. Robustness checks were performed with other interest rate variables (CMT-1, CMT-10, and Chicago Federal Reserve farm loan rate) and the model was also run on different timelines to ensure robustness of results.

Empirical Results and Discussion

The model was estimated by means of ordinary least squares (OLS) regression. The results (displayed in Table 3) indicated a positive relationship between farmland values and gross farm income, a finding consistent with previous literature (Chryst, 1965; Featherstone et al., 2017; Reinsel & Reinsel, 1979; Reynolds & Timmons, 1969). Results also indicated that interest rates and farmland values were inversely related as previously reported (Burt, 1986; Moss, 1997; Nickerson & Zhang, 2014; Sherrick, 2018; Zhang & Tidgren, 2018).

The general form of the derived models was a first-order ARDL (p,q;n), where *p* is the number of lags of $\mathrm{Y_t}$, q is the number of lags of $\mathrm{X_t}$, and *n* is the number of the regressors. The ARDL model in this study has the following form (De Boef & Keele, 2008; Bardsen, 1989):

(12) $$\mathrm{Y_t} = \alpha_0 + \sum_{i=1}^{p} \alpha_i \mathrm{Y}_{t-i} + \sum_{j=1}^{n}\sum_{i=0}^{q} \beta_{jp}\mathrm{X}_{jt-i} + \delta_{it} + \gamma_{it} + \epsilon_{it}$$

where, Y is inflation-adjusted farmland value, X_1 is the real federal funds rate, X_2 is inflation-adjusted gross farm income, δ_{it} is the time-invariant individual unobserved effect, γ_{it} accounts for a linear trend, and ϵ_{it} is the error term. To ensure stationarity of $\mathrm{Y_t}$, it is required that $\left|\sum_{i=1}^{p} \alpha_i\right| < 1$ (De Boef & Keele, 2008). The model in this study was an ARDL (1,1;2) model where the lags of the dependent variable equaled the lags of the regressors. The model expanded into equation (13):

(13) $$\mathrm{Y_t} = \alpha_0 + \alpha_1 \mathrm{Y}_{(t-1)} + \beta_{10}\mathrm{X}_{1(t)} + \beta_{11}\mathrm{X}_{1(t-1)} + \beta_{20}\mathrm{X}_{2(t)} + \beta_{21}\mathrm{X}_{2(t-1)} + \delta_{it} + \gamma_{it} + \epsilon_{it}$$

Results indicated strong significance (at 99% confidence level) for the effects of lagged land values in explaining current farmland values for the three regions. Additionally, the effect of lagged land values was positive as had been previously reported (Featherstone et al., 2017). The magnitude of the lagged land values effect (coupled with the relatively small farm income effect) reflected potential absorption of the farm income effects on farmland values (regression analysis excluding lagged land values indicated a stronger and more significant effect of gross farm income in farmland values at time t; see results in appendix A).

The effect of real interest rates at time *t* in farmland values was negative and significant (at 99% confidence level) for the I-states and Great Plains regions. The interest rate effect at time *t* for the Lakes region was also negative but insignificant. The lagged real interest rate coefficients were significant and negative for the three regions at the 99% level. Likewise, farm income appeared significant at the 99% confidence levels for all three regions. Lagged farm income effects appeared insignificant for all three regions, and there was a reverse sign for the lagged farm income effect in the Lakes region regression - contrary to what is expected from the published literature.

Table 3. OLS Estimates for the Main Specification ARDL(1,1;2)

	I-States $Land_{(t)}$	Lakes $Land_{(t)}$	G.Plains $Land_{(t)}$
$Land_{(t-1)}$	0.884***	0.922***	0.939***
	(0.016)	(0.024)	(0.008)
Real Interest $Rate_{(t)}$	-0.890*	-0.317	-0.914***
	(0.224)	(0.334)	(0.154)
Real Interest $Rate_{(t-1)}$	-2.004***	-1.659***	-1.732***
	(0.113)	(0.138)	(0.122)
Farm $Income_{(t)}$	0.175***	0.248***	0.095***
	(0.016)	(0.029)	(0.016)
Farm $Income_{(t-1)}$	0.011	-0.133	0.053
	(0.027)	(0.088)	(0.028)
Constant	2.112	1.561	7.010**
	(1.311)	(2.066)	(1.852)
Obs.	159	212	265
R-squared	0.994	0.995	0.994
Linear Trend	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes
Robust Standard Errors	Yes	Yes	Yes

Note: Robust standard errors are in parenthesis.
*** $p<0.01$, ** $p<0.05$, * $p<0.10$

The ARDL model accounts for long and short-term effects; therefore, joint significance tests were performed (results in appendix B) that indicated independent variables and their lags are jointly significant for all regions despite particular individual insignificances. Hence, those variables were kept in the final model.

Long-Run Effects and Median Lag Lengths

A common potential error made by researchers when selecting, estimating, and making inferences based on the results of an ARDL model is that interpretations of the magnitude of the effects are strictly limited to short-run effects (as would be the case in a static model), thereby ignoring long-run effects of such changes in the variable of interest (De Boef & Keele, 2008). In this study, short-term or immediate effects of farm income and interest rates on farmland values were estimated by the coefficients (for explanatory variable effect at time t) in the ARDL model of all three regions. The model estimated that a one-percentage point increase in the federal funds rate decreases farmland values in the same year by 0.89% and 0.91% in the I-States and Great Plains regions, respectively; a 1% increase in farm income increases farmland values by 0.17%, 0.25%, and 0.1% in the I-States, Lakes, and Great Plains, respectively.

To calculate long-term effects, the assumption that two time-series are in equilibrium and converge in the long-run must hold and the time-series converges to the following ARDL (1,1;1) $\mathrm{Y}^* = \alpha_0 + \alpha_1 \mathrm{Y}^* + \beta_0 \mathrm{X}^* + \beta_1 \mathrm{X}^*$ (De Boef & Keele, 2008)

Solving for Y^* in terms of X^* equates (De Boef & Keele, 2008):

(14) $$\mathrm{Y}^* = \frac{\alpha_0}{1-\alpha_1} + \frac{\beta_{10}+\beta_{11}}{1-\alpha_1}\mathrm{X}_1^* + \frac{\beta_{20}+\beta_{21}}{1-\alpha_1}\mathrm{X}_2^* = \mathrm{k}_0 + \mathrm{k}_{11}\mathrm{X}_1^* + \mathrm{k}_{12}\mathrm{X}_2^*$$

where k_{i1} yields the long-run multiplier (LRM) of X_{it} with respect to Y_t, or the cumulative effect of X_{it} on Y_t distributed across time periods (De Boef & Keele, 2008). The error correction rate, also referred to as the speed of adjustment, is a measure of how Y_t changes across time periods (De Boef & Keele, 2008; Tweeten & Martin, 1966).

Table 4 reports the results of the long-run multipliers and the error correction rate (ECR) for real interest rates and inflation-adjusted gross farm income. The long-run multipliers are simply the long-run cumulative effects (distributed across time periods) induced by unit changes in regressors (De Boef & Keele, 2008; Tweeten & Martin, 1966). The Great Plains region reports a larger long-run multiplier, potentially as a result of slower rates of error correction (due to large coefficient for the lagged land value α_1). This indicates that lags necessary for adjustment will be larger. The error correction rate, however, is the same for both regressors because it takes into account only the coefficient of the lagged farmland value (α_1).

Table 4. Long-Run Multipliers (LRM) and Error Correction Rates (ECR)

	I-States	Lakes	N. Plains
Interest Rates			
Long-run multiplier k_{11}	24.95	25.33	43.38
Farm Income			
Long-run multiplier k_{21}	1.60	1.47	2.43
Error correction rates	0.12	0.08	0.06

The median lag length provides relevant information on the lag distribution of the X_ts and the first lag, noted as r, at which half of the adjustment, induced by the shocks of a unit change in X_t, has already occurred (De Boef & Keele, 2008).

Median lag lengths of the effects of real interest rate and inflation-adjusted gross farm income on farmland values were calculated using De Boef and Keele's (2008) methodology. The median lag was calculated by identifying individual effects at each lag, standardizing them as proportions of the cumulative effect (LRM)[1], and identifying the lag when the sum of individual effects exceeds half of the cumulative effect.

[1] Normalization process (standardization of individual lag effects) is shown in appendix C.

The formula represented in equation (15) may be used to generate the median lags for both regressors – interest rates and farm income:

$$A(L)Y_t = B(L)X_t + \epsilon_t \tag{15}$$

where L represents the lag operator ($L_i X_t = X_{t-1}$), $A(L) = 1 - \alpha_1 L - \alpha_2 L^2 - \cdots - \alpha_p L^p$ and $B(L) = \beta_0 + \beta_1 L + \beta_2 L^2 + \cdots + \beta_q L^q$. The median lag is obtained when the value of m, represented by equation (16), is greater than or equal to 0.50 (i.e., $m \geq 0.50$) (De Boef & Keele, 2008).

$$m = \frac{\sum_{r=0}^{R} \omega_r}{\sum_{r=0}^{\infty} \omega_r} = \frac{\sum_{r=0}^{R} \omega_r}{\dfrac{\sum_{i=0}^{q} \beta_i}{1 - \sum_{i=0}^{p} \alpha_i}} = \frac{\sum_{r=0}^{R} \omega_r}{k_{i1}} \tag{16}$$

In equation (16), the denominator represents the long-run multiplier or k_{i1}. The numerator represents effects throughout any periods, *R*, where ω_r is the individual magnitude of the effect in period *r* (De Boef & Keele, 2008). The operation in equation (16) allows standardization of individual effects with respect to the cumulative effect.

Identification of individual lag effects, normalization, and notation of the proportion of each individual effect on the cumulative effect were calculated separately for both real federal funds rate and inflation-adjusted gross farm income (Table 5).

Calculations[2] indicated that the median lag length for interest rate (gross farm income) effect in the I-States, Lakes, and Great Plains regressions were six, nine, and eleven (five, seven, and eleven) lags, respectively (Figure 3 and 4; Table 5).

[2] Methodology follows De Boef and Keele (2008); general form shown in appendix C.

Table 5. Long-term Effects and Median Lag Lengths by Region

	I-States		Lakes		Great Plains	
	Interest Rate					
Lags	Magnitude of Effect	Percent of Cumulative	Magnitude of Effect	Percent of Cumulative	Magnitude of Effect	Percent of Cumulative
0	-0.89	3.57%	-0.32	1.25%	-0.91	2.11%
1	-2.79	11.19%	-1.95	7.70%	-2.59	5.97%
2	-2.47	9.89%	-1.80	7.10%	-2.43	5.61%
3	-2.18	8.74%	-1.66	6.55%	-2.28	5.27%
4	-1.93	7.73%	-1.53	6.04%	-2.14	4.94%
5	-1.70	6.83%	-1.41	5.57%	-2.01	4.64%
6	-1.51	6.04%	-1.30	5.13%	-1.89	4.36%
7			-1.20	4.73%	-1.78	4.09%
8			-1.11	4.36%	-1.67	3.84%
9			-1.02	4.02%	-1.57	3.61%
10					-1.47	3.39%
11					-1.38	3.18%
		53.98%		**52.45%**		**51.01%**
	I-States		Lakes		Great Plains	
	Farm Income					
Time	Effect of Magnitude	Percent of Cumulative	Effect of Magnitude	Percent of Cumulative	Effect of Magnitude	Percent of Cumulative
0	0.18	10.91%	0.25	16.82%	0.10	3.92%
1	0.17	10.33%	0.10	6.49%	0.14	5.86%
2	0.15	9.14%	0.09	5.98%	0.13	5.50%
3	0.13	8.08%	0.08	5.52%	0.13	5.17%
4	0.11	7.14%	0.07	5.09%	0.12	4.85%
5	0.10	6.31%	0.07	4.69%	0.11	4.56%
6			0.06	4.32%	0.10	4.28%
7			0.06	3.99%	0.10	4.02%
8					0.09	3.77%
9					0.09	3.54%
10					0.08	3.33%
11					0.08	3.12%
		51.91%		**52.89%**		**51.92%**

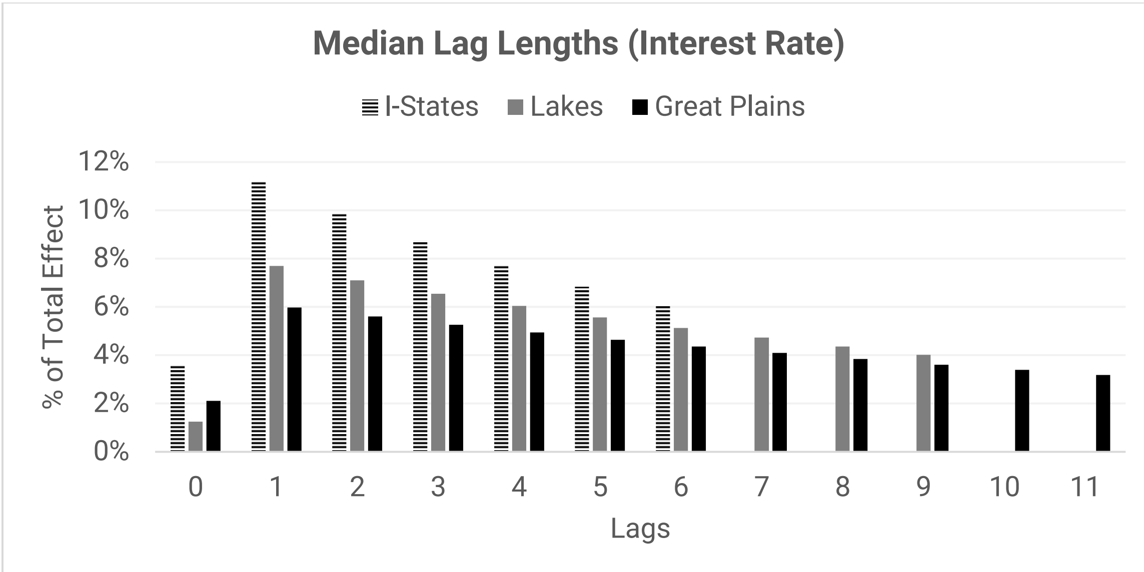

Figure 3. **Median lag lengths for interest rate effects by region.**

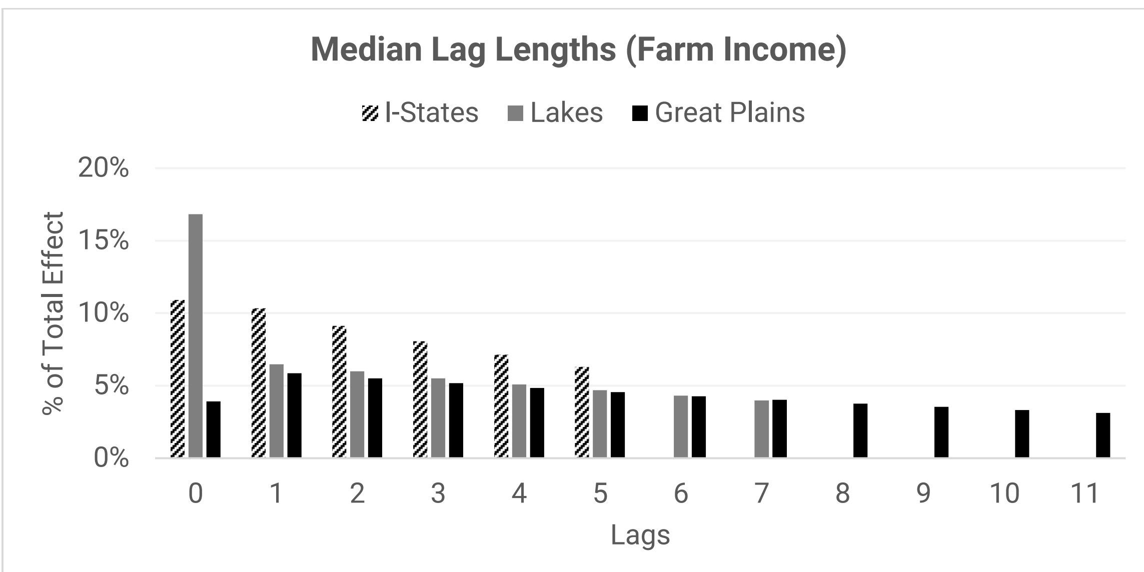

Figure 4. Median lag length for farm income effects by region.

The interest rate effect in the first lag is the strongest, and the effects are smaller in subsequent years. For gross farm income effects, however, the immediate shock comprises the largest effect (excluding Great Plains) as a percentage of the total effect (i.e., LRM). In the Great Plains, farm income effects mimic interest rate effects – large effect in the first lag but declining thereafter.

Previous empirical farmland value models used aggregate United States or state-specific data, and not all studies used farm income as an explanatory variable. Instead variables considered as a proxy for farm income (i.e., rents, personal income) were used. Results of this study are consistent with previous literature (taking into account the fact that variables being compared are not the same). In one study, the effect of net rents on farmland values (double-log form) was positive and its magnitude was 0.04 (Klinefelter, 1973), which is consistent with the ARDL model in this study. Additionally, in a more recent study on Illinois farmland prices, the effects of personal income (no farm income used in the model) ranged from 0.47% (by maximum likelihood estimator) to 0.63% (by OLS) (Huang et al., 2006), which is higher than what was found by the ARDL model but comparable given coefficients in the Huang et. al (2006) paper did not utilize farm income directly. Perhaps the most consistent result would be the elasticity of land price with respect to net farm income (0.086) in Tweeten and Martin (1966), which is highly similar to the coefficients of gross farm income estimated in this model.

Results of interest rate effects on farmland values in this study were also fairly consistent with previous literature. The effect of the capitalization rate in Reynolds and Timmons (1969) was negative, as found in this study, but much larger in magnitude (-5.73). However, it should be noted that this study estimates a dynamic model which takes into account effects in more than one period of time, which could explain why the estimates are much smaller than in Reynolds and Timmons (1969). Shaik et al. (2005)

found that a 10% increase in the real interest rate decreases farmland values by 2.5%, (we find that the one-unit change in the federal funds rate would lead to an 25% overall decline in farmland values for two of our regions and a 43% decline in the other region).

Deriving an Error Correction Model (ECM) from the ADRL Model

To check for robustness of the results obtained with the ARDL (1,1;2) model, an ECM was developed. The ECM ensured that data were stationary. The ECM has the following form (De Boef & Keele, 2008):

$$(17) \quad \Delta Y_t = \alpha_0 + \alpha_1^* Y_{(t-1)} + \beta_{10}^* \Delta X_{1(t)} + \beta_{11}^* X_{1(t-1)} + \beta_{20}^* \Delta X_{2(t)} + \beta_{21}^* X_{2(t-1)} + \delta_{it} + \gamma_{it} + \epsilon_{it}$$

The results of the ECM are displayed in the last three columns of Table 6 (for comparison purposes, the results of the ADRL also are displayed). Simple mathematical operations and substitution indicates consistency of the ARDL and ECM (Bardsen, 1989; De Boef & Keele, 2008). Following methodology discussed in De Boef and Keele (2008), in the ECM model, α_1^* was the equivalent of $(\alpha_1 - 1)$ in the ARDL; or $(0.884 - 1) = -0.116$ for I-States, $(0.922 - 1) = -0.078$ for Lakes, and $(0.939 - 1) = -0.061$ for the Great Plains. Because the ECM expressed dependent and independent variables as differenced variables, the estimates of these variables should be the same in ECM as they were in ARDL; therefore, $\beta_{i0} = \beta_{i0}^*$, for $i = 1{,}2$, in all three instances.

Lastly, the effects of the lags of regressors were obtained by adding both ARDL estimates of the independent variables, or $\beta_i^* = (\beta_{i0} + \beta_{i1})$, for $i = 1{,}2$, in all three instances. Basic mathematical operations support these claims for the three regressions estimated. The long-run multipliers were consistent when calculated with results obtained from the ARDL and those obtained from the ECM. The formula that was used to calculate long-run multipliers with an ECM model was $k_{i1_{ECM}} = \frac{\beta^*_{i1}}{-\alpha_1}$ (De Boef & Keele, 2008). Results of the ARDL being consistent with those of the ECM suggests that stationarity was not an issue; therefore, because the ARDL had a significantly higher R^2, it remained as the main specification of this study.

Table 6. Regression Estimates for ARDL (first three columns) and ECM (last three columns)

	I-States $Land_{(t)}$	Lakes $Land_{(t)}$	G.Plains $Land_{(t)}$	I-States $\Delta Land_{(t)}$	Lakes $\Delta Land_{(t)}$	G.Plains $\Delta Land_{(t)}$
$Land_{(t-1)}$	0.884***	0.922***	0.939***	-0.116**	-0.078**	-0.061***
	(0.016)	(0.024)	(0.008)	(0.016)	(0.024)	(0.008)
Interest $Rate_{(t)}$	-0.890*	-0.317	-0.914***			
	(0.224)	(0.334)	(0.154)			
Interest $Rate_{(t-1)}$	-2.004***	-1.659***	-1.732***	-2.894***	-1.976**	-2.646***
	(0.113)	(0.138)	(0.122)	(0.228)	(0.446)	(0.232)
Farm $Income_{(t)}$	0.175***	0.248***	0.095***			
	(0.016)	(0.029)	(0.016)			
Farm $Income_{(t-1)}$	0.011	-0.133	0.053	0.186**	0.115	0.148***
	(0.027)	(0.088)	(0.028)	(0.040)	(0.061)	(0.025)
Δ Interest Rate				-0.890*	-0.317	-0.914***
				(0.224)	(0.334)	(0.154)
Δ Farm Income				0.175***	0.248***	0.095***
				(0.016)	(0.029)	(0.016)
Constant	2.112	1.561	7.010**	2.112	1.561	7.010**
	(1.311)	(2.066)	(1.852)	(1.311)	(2.066)	(1.852)
Obs.	159	212	265	159	212	265
R-squared	0.994	0.995	0.994	0.507	0.388	0.440
Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
LRM / k_{11}	24.95	25.33	43.38	24.95	25.33	43.38
LRM / k_{21}	1.60	1.47	2.43	1.60	1.47	2.43

Note: Robust standard errors are in parenthesis.
*** p<0.01, ** p<0.05, * p<0.10

Prediction Power of the Autoregressive Distributed Lag (ARDL) Models

Given that the ARDL model was selected as the main specification for this study, its validity was tested for its within-sample estimation (results in appendix D) and out-of-sample forecasting ability. The high R^2 for all three regression models indicated that the variation in farmland value was captured extremely well with those regressors.

Results for the I-States Regression Prediction

The regression results for the I-States indicated significance for both interest rate (90% confidence level) and farm income effects (99% confidence level), and significance only for the lagged interest rate effect (99% confidence level). Figure 5 depicts actual farmland values for the I-States plotted against the predicted values in both logarithmic scale (panel A) and dollars/acre (panel B).

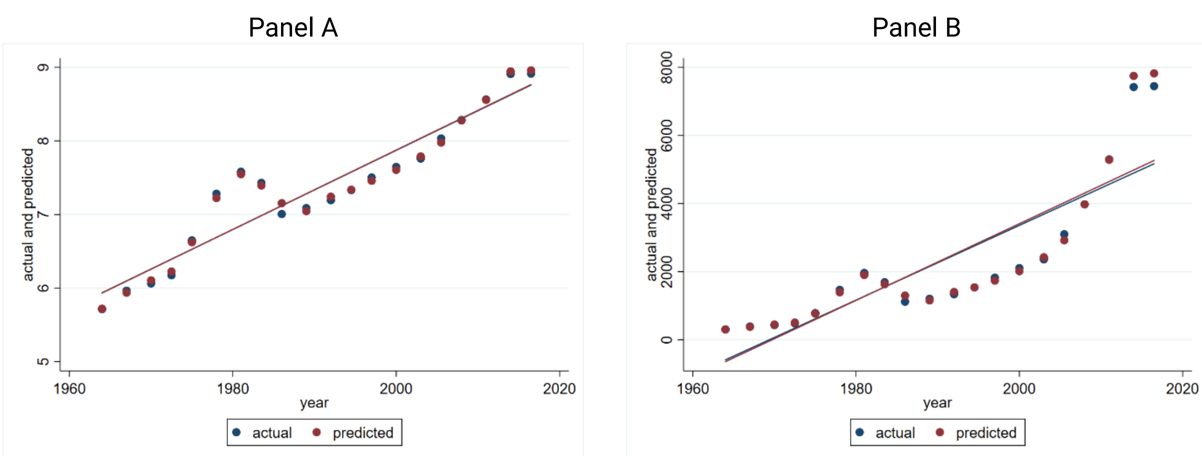

Figure 5. Actual and predicted farmland values (in logarithms [panel a] and $/acre [panel b]) for the I-States.

Figure 5 shows that the model performed well, and that predicted values were consistently nearly equal to actual observations of farmland values in the I-States. The model also captured well the trend before and after the 1980s farm crisis. Table 7 displays out-of-sample summary statistics for differences between the actual and predicted farmland values. The model incorrectly predicted with an average residual of $20.69/acre and a standard deviation of $271.19/acre.

Table 7. Descriptive Statistics for the Forecast Errors (I-States)

Variable	Obs[3]	Mean	Std.Dev.	Min	Max
Forecast Errors	165	20.69	271.19	-569.74	1781.67

Table 8 and Figure 6 display specific information regarding the predictive power of the model for the I-States regression. On average, the model predicted with an accuracy of 93.3%.

Table 8. Prediction of Farmland Values for 2016 and 2017 (I-States)

State	Year	Actual Land Value	Predicted Land Value	Difference	Percent Accuracy
Illinois	2016	7400.00	7714.00	314.00	95.76%
Illinois	2017	7300.00	7733.70	433.70	94.06%
Indiana	2016	7150.00	6812.69	-337.31	95.28%
Indiana	2017	7000.00	6909.19	-90.81	98.70%
Iowa	2016	7850.00	8880.07	1030.07	86.88%
Iowa	2017	8000.00	8894.40	894.40	88.82%

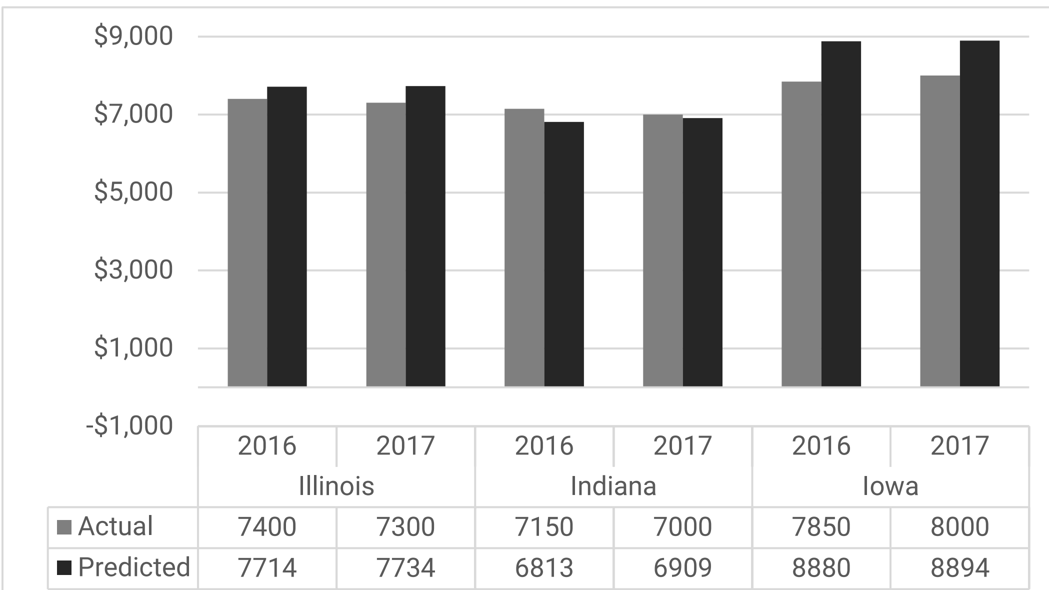

Figure 6. Actual vs. predicted farmland values for the I-States (2016, 2017)

The accuracy of prediction is calculated by expressing prediction errors (absolute value of the difference between the actual and predicted land value at time *t*

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[3] Larger number of observations than those used to run the model because of out-of-sample forecasting

divided by the actual land value at time *t*) in percentage terms. For instance, the 2017 predicted land value for Indiana was $6909/acre, while the actual land value was $7000/acre (a difference of $91/acre). In this case, the model predicted incorrectly by 1.3% (meaning it was 98.7% accurate).

Results for the Lakes Regression Prediction

The results for the Lakes region showed 99% significance level for lagged interest rate and farm income, but no significance for lagged farm income or interest rate. Figure 7 depicts actual farmland values for the Lakes region plotted against the predicted values in both logarithmic scale (panel A) and dollars/acre (panel B).

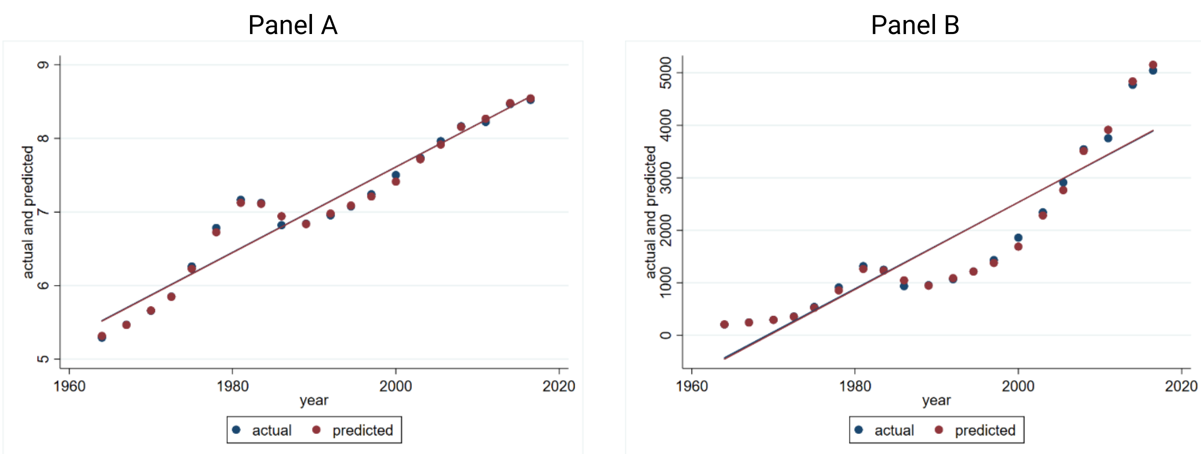

Figure 7. Actual and predicted farmland values (in logarithms [panel a] and $/acre [panel b]) for the Lakes region.

Figure 7 shows that the model performed well, and that predicted farmland values were consistently nearly equal to the actual farmland values in the Lakes region. Out-of-sample summary statistics for differences between the actual and predicted farmland values are displayed in Table 9. The model incorrectly predicted with an average residual of $7.52/acre (a negative mean signals that this model underestimates more relative to the other two models) and a standard deviation of $151.17/acre.

Table 9. Descriptive Statistics for the Forecast Errors (Lakes region)

Variable	Obs	Mean	Std.Dev.	Min	Max
Forecast Errors	220	-7.52	151.17	-484.71	651.51

Table 10 and Figure 8 display information regarding the predictive power of the model for the Lakes region. On average, the model predicted with an accuracy of 96.6% – the best performing model of the three developed in this study.

Table 10. Prediction of Farmland Values for 2016 and 2017 (Lakes region)

State	Year	Actual Land Value	Predicted Land Value	Difference	Percent Accuracy
Ohio	2016	5700.00	5675.96	-24.04	99.58%
Ohio	2017	5650.00	5766.42	116.42	97.94%
Michigan	2016	4800.00	4783.82	-16.18	99.66%
Michigan	2017	4800.00	4784.21	-15.79	99.67%
Minnesota	2016	4700.00	5110.78	410.78	91.26%
Minnesota	2017	4750.00	5214.30	464.30	90.23%
Wisconsin	2016	4750.00	4857.75	107.75	97.73%
Wisconsin	2017	5200.00	5020.40	-179.60	96.55%

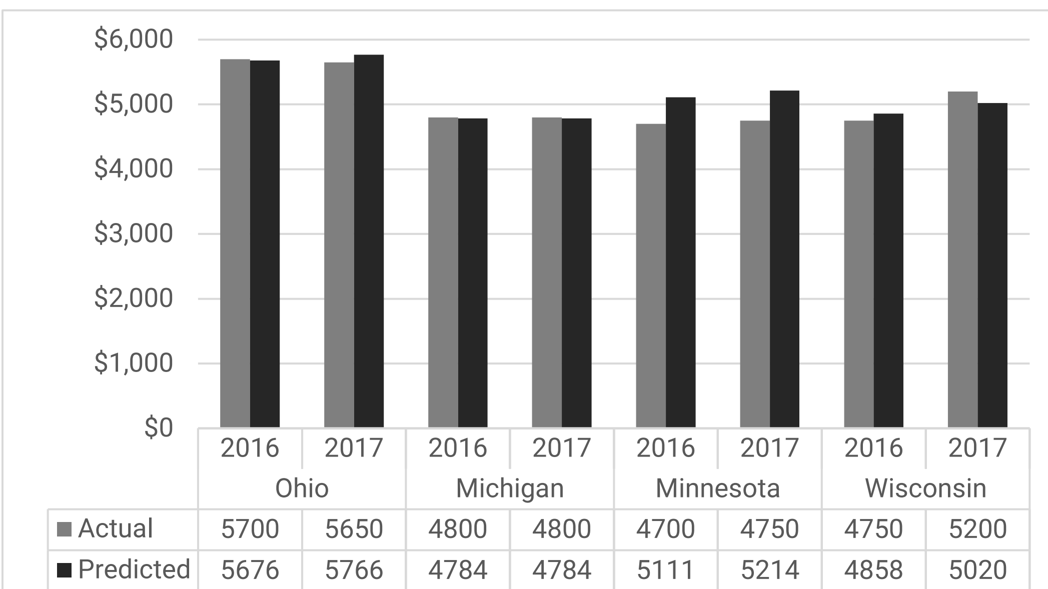

Figure 8. Actual vs. predicted farmland values for the Lakes region (2016, 2017)

Results for the Great Plains Regression Prediction

The regression results for the Great Plains region indicate 99% significance for interest rate, lagged interest rate, and farm income (lagged farm income is insignificant in this model). Figure 9 depicts actual farmland values for the Great Plains region plotted against the predicted values in both logarithmic scale (panel A) and dollars/acre level (panel B).

Panel A Panel B

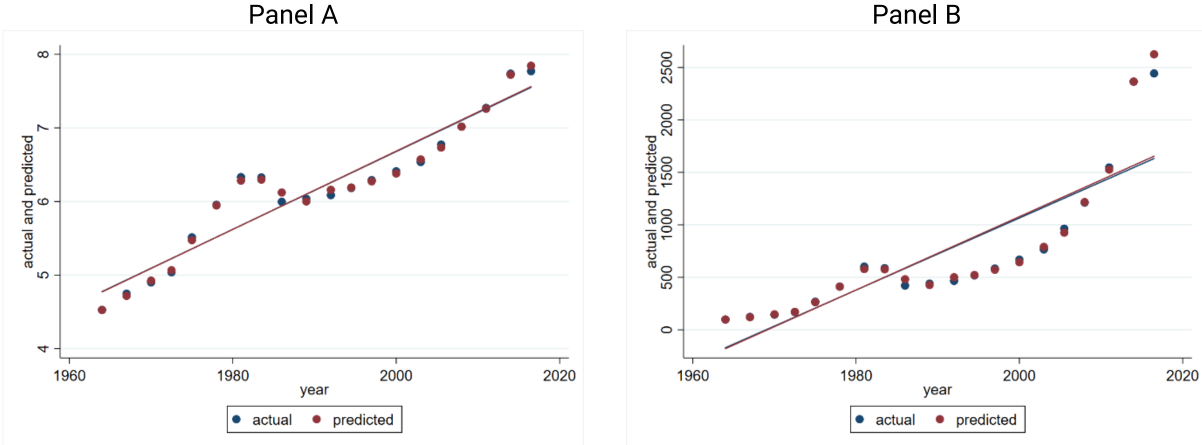

Figure 9. Actual and predicted farmland values (in logarithms [panel a] and $/acre [panel b]) for the Great Plains region.

Figure 9 shows that the model performed well and that predicted values are consistently nearly equal to actual farmland values in the Great Plains. After the 1980s farm crisis, the model predicted incorrectly for a few years; however, it corrected its predictions thereafter. The evident outlier was 2017, where the model substantially overestimated.

Table 11 displays out-of-sample summary statistics for differences between actual and predicted farmland values. The model incorrectly predicted an average residual of $6.53/acre and a standard deviation of $87.38/acre.

Table 11. Descriptive Statistics for the Forecast Errors (Great Plains)

Variable	Obs	Mean	Std.Dev.	Min	Max
Forecast Errors	275	6.53	87.38	-323.21	553.62

Table 12 and Figure 10 display information on the predictive power of the model for the Great Plains region. On average, the model predicted with an accuracy of 91.7%. The model for Great Plains systematically overestimated farmland values for 2016 and 2017 (except for the Missouri 2016 farmland value prediction).

Table 12. Prediction of Farmland Values for 2016 and 2017 (Great Plains)

State	Year	Actual Land Value	Predicted Land Value	Difference	Percent Accuracy
Missouri	2016	3400.00	3326.16	-73.84	97.83%
Missouri	2017	3350.00	3435.26	85.26	97.45%
Kansas	2016	1880.00	2219.97	339.97	81.92%
Kansas	2017	1850.00	2088.37	238.37	87.12%
Nebraska	2016	2950.00	3406.14	456.14	84.54%
Nebraska	2017	2900.00	3334.29	434.29	85.02%
North Dakota	2016	1830.00	1931.93	101.93	94.43%
North Dakota	2017	1840.00	1869.02	29.02	98.42%
South Dakota	2016	2250.00	2342.93	92.93	95.87%
South Dakota	2017	2180.00	2299.40	119.40	94.52%

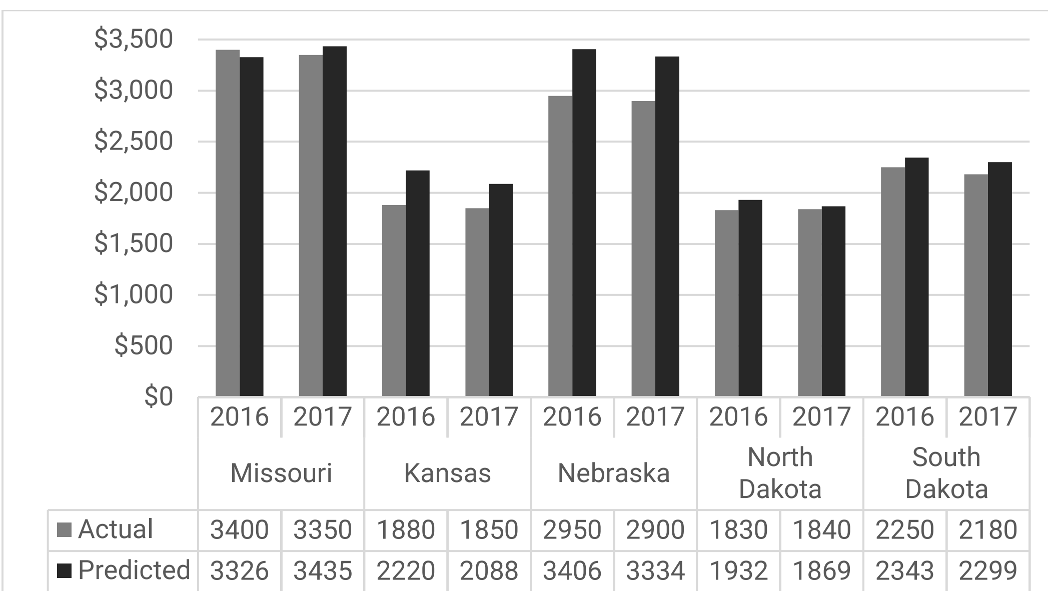

Figure 10. Actual vs. predicted farmland values for the Great Plains region (2016, 2017)

Policy Implications

Because the federal funds rate is used as the interest rate variable, future predictions of farmland value changes due to interest rate policy are easily calculated. Keeping the 2017 federal funds rate as the base level (1.00%), an increase to 1.83% in 2018 would imply a unit change in interest rate of 0.83 percentage points. For the I-States, according to the regression results, this change in interest rate would translate to (-0.890)(0.83) or a 0.74% decline in farmland values. For the Lakes and Great Plains regions, the drop due to a 0.83-percentage-point increase in the interest rate will decrease farmland values by 0.26% and 0.76% respectively (it should be noted that, although the interest rate variable shows insignificant in the Lakes regression model, it is kept because of joint significance). Table 13 shows predictions for 2018 farmland values taking into account a 0.83-percentage-point increase in the federal funds rate only (keeping other variables constant in the model).

The ARDL model is only capable of predicting decreases as a result of increases in interest rates (due to the inversely correlated relationship); however, farmland values in half of the states (Illinois, Indiana, Iowa, Missouri, Ohio, Wisconsin) experienced growth from previous years (potentially due to the factors that were kept constant when predicting). For the remaining states which experienced declines in farmland values, the model predicted values close to the actual 2018 land values. For instance, the closest prediction corresponds to North Dakota – the model predicted $1826/acre, whereas the actual value was $1830/acre (the prediction was off by $4/acre).

Table 13. Farmland Value Predictions for 2018 due to Interest Rate Changes

	2017 Actual Land Value	2018 Predicted Land Value	2018 Actual Land Value	Difference between Predicted and Actual	Predicted Change in 2018	Actual Change in 2018	Overall Model Accuracy
I-States							
Illinois	7300	7246	7450	-204	-0.74%	2.05%	97.26%
Indiana	7000	6948	7100	-152	-0.74%	1.43%	97.86%
Iowa	8000	7941	8080	-139	-0.74%	1.00%	98.28%
Lakes							
Ohio	5650	5635	5740	-105	-0.26%	1.59%	98.17%
Michigan	4800	4787	4780	7	-0.26%	-0.42%	99.85%
Minnesota	4750	4738	4700	38	-0.26%	-1.05%	99.20%
Wisconsin	5200	5186	5320	-134	-0.26%	2.31%	97.49%
Great Plains							
Missouri	3350	3325	3700	-375	-0.76%	10.45%	89.85%
Kansas	1850	1836	1800	36	-0.76%	-2.70%	98.00%
Nebraska	2900	2878	2850	28	-0.76%	-1.72%	99.02%
North Dakota	1840	1826	1830	-4	-0.76%	-0.54%	99.78%
South Dakota	2180	2163	2170	-7	-0.76%	-0.46%	99.70%

In eight of the twelve states, the model under-predicted, which may be a result of simultaneous gross farm income changes that are otherwise considered constant in these predictions. It is impossible to combine both interest rate effects and gross farm income changes as the 2018 state-level gross farm income data is not yet accessible.

Further projected increases of the federal funds rate (Federal Reserve, 2019) as evident by the most recent Federal Reserve Dot Plot in March 2019 indicate that future declines in farmland values may occur. Assuming the federal funds rate increases to 3.00%, the declines in farmland values in the I-States and Great Plains would be 0.15% and 0.16% respectively (due to an increase of 0.17 percentage points in interest rate; keeping 2018 federal funds rate as the base level). If the federal funds rate increases to

3.5%, it would imply an increase of 0.67 percentage points when keeping the 2018 rate as the base level. This increase in interest rate would decrease farmland values by 0.60% and 0.61% in I-States and Great Plains, respectively.

Trade policy effects may also be incorporated into the model through rises or declines in gross farm income. Focusing specifically on the I-States, we can present farm income changes based solely on the relationship of farm income in the I-States and aggregate United States. Over the course of 55 years, gross farm income generated in the I-States averaged 4.86% of total U.S. gross farm income. Based on this observation, it can be speculated that average gross farm income in the I-States in 2018 will be 4.86% of the total U.S. gross farm income, or $21.04 billion. This implies an increase in I-States gross farm income of 5.5% (from $19.94 billion in 2017 to $21.04 billion in 2018). The ARDL model can, as a result, imply that farmland values should increase by 0.96% in the I-States, which when combined with interest rate changes offsets the immediate decline in farmland values induced solely by interest rate changes. In this I-States case, simultaneous changes in the regressors would lead to the net immediate effect of a 0.22% projected increase in farmland values, which is closer to actual 2018 values than those presented in Table 13 (recall the I-States experienced a mean increase of 1.49% in 2018 land value).

Following the same logic of calculations, the gross farm incomes generated in the Lakes and Great Plains averaged 3.00% and 3.12% of the total U.S. gross farm income, respectively. As a result, it can be speculated that 2018 gross farm income would be $13.0 billion and $13.8 billion in the Lakes and Great Plains, respectively. The average 2017 gross farm income of four states in the Lakes region was $12.5 billion, which indicates an increase of 4% in gross farm income within this region in 2018. With this increase in gross farm income, the ARDL model projects a 0.99% increase in the Lakes farmland values, which may possibly explain the increase of 2.31% and 1.59% in Wisconsin and Ohio land values, respectively, in 2018 (however, land values in Michigan and Minnesota actually decreased by 0.42% and 1.05%, respectively). On the other hand, the average 2017 gross farm income of the five states in the Great Plains region was $14.7 billion, which indicates a decline of 6.52% in gross farm income within this region in 2018. According to ARDL regression results, such a decline in Great Plains gross farm income would immediately decrease farmland values by 0.62%. Recall from Table 13 that farmland values within this region experienced an average 1.36% decline in farmland values (with the exception of Missouri's land value which increased 10.45%). Effects of declines in gross farm income coupled with rising federal funds rate in 2018 explain the actual 2018 decreases in the Great Plains farmland values.

Robustness Checks

In addition to the out-of-sample forecasting validation, other robustness checks were performed. The first robustness check performed involved running the regression models with an alternative measure for interest rates –the real one-year Treasury Constant Maturity Rate (CMT-1). The results are displayed in Table 14.

Great consistency was noted between the results of the ARDL model using the federal funds rate as the real interest rate and those of the ARDL model using CMT-1 as the real interest rate. The lagged land value coefficients appeared highly similar, and the lagged interest rate coefficients in the I-States was underestimated compared to the model with the federal funds rate (perhaps to correct for the larger magnitude of the coefficient of interest rate at time t).

Table 14. Results for ARDL w/ Federal Funds Rate (first three columns) and ARDL w/ CMT-1 as Real Interest Rates (last three columns)

	I-States Land$_{(t)}$	Lakes Land$_{(t)}$	G.Plains Land$_{(t)}$	I-States Land$_{(t)}$	Lakes Land$_{(t)}$	G.Plains Land$_{(t)}$
Land$_{(t-1)}$	0.884***	0.922***	0.939***	0.889***	0.927***	0.951***
	(0.016)	(0.024)	(0.008)	(0.010)	(0.026)	(0.011)
Fed Funds Rate$_{(t)}$	-0.890*	-0.317	-0.914***			
	(0.224)	(0.334)	(0.154)			
Fed Funds Rate$_{(t-1)}$	-2.004***	-1.659***	-1.732***			
	(0.113)	(0.138)	(0.122)			
CMT-1$_{(t)}$				-1.121***	-0.340	-1.187***
				(0.131)	(0.394)	(0.082)
CMT-1$_{(t-1)}$				-1.493***	-1.658**	-1.789***
				(0.192)	(0.294)	(0.116)
Farm Income$_{(t)}$	0.175***	0.248***	0.095***	0.154***	0.246**	0.095***
	(0.016)	(0.029)	(0.016)	(0.017)	(0.048)	(0.013)
Farm Income$_{(t-1)}$	0.011	-0.133	0.053	0.012	-0.156	0.032
	(0.027)	(0.088)	(0.028)	(0.025)	(0.116)	(0.034)
Constant	2.112	1.561	7.010**	1.419	0.059	6.869**
	(1.311)	(2.066)	(1.852)	(0.825)	(2.521)	(1.332)
Obs.	159	212	265	265	265	212
R-squared	0.994	0.995	0.994	0.994	0.996	0.995
Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
LRM / k_{11}	24.95	25.33	43.38	23.55	27.37	60.73
LRM / k_{21}	1.60	1.47	2.43	1.50	1.23	2.59

Note: Robust standard errors are in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Additionally, lagged farm income results were consistently insignificant across both specifications, and the Lakes regression reported the lagged farm income was negative in both instances. The long-run multipliers were similar for the I-States and Lakes regions in both specifications; however, the long-run multiplier for the Great Plains region was larger in the CMT-1 specification. This result was driven mainly by the smaller error correction rate (or the magnitude in the denominator of k_{11}) considering the sum of the coefficients of the interest rate variables in the CMT-1 specification is smaller (2.614) than that in the main specification using the federal funds rate as the interest rate variable (2.894).

The second robustness check included was running the model with 1963-2017 data, testing the within-sample estimation power (summary statistics of prediction errors [appendix E] and predicted farmland values for years 2016 and 2017 [appendix F]), and comparing it to the main model of this study. The regression results are displayed in Table 15. Overall, there were no changes in the direction of the effects; however, there were some noticeable changes in the magnitude of short-term effects, especially for the Great Plains regression, driven by the inclusion of the additional two years (2016, 2017). The within-sample predictions for 2016 and 2017 performed with the specification that included observations from 1963 to 2017 were not significantly closer to actual farmland values for all of the states in all three regions than were the out-of-sample predictions performed for 2016 and 2017 using only data from 1962 to 2015. With the new specification, on average, the I-States, Lakes, and Great Plains models predicted with an accuracy of 93.5%, 96.9%, and 93.6%, respectively (compared to 93.2%, 96.6%, and 91.7%, respectively, with the main model).

The Great Plains region had the largest gain from the new specification considering that predictions were better and the long-run multiplier for the interest rate effects, k_{11}, encountered a drop from the main model estimation and became more aligned with the two other regions (Table 15). This finding indicated that the lags necessary for half of the interest rate effect to be dissipated are smaller, and, therefore, the effect will adjust more quickly.

Table 15. ARDL (1963-2015; first three columns) and ARDL (1963-2017; last three columns)

	I-States $Land_{(t)}$	Lakes $Land_{(t)}$	G.Plains $Land_{(t)}$	I-States $Land_{(t)}$	Lakes $Land_{(t)}$	G.Plains $Land_{(t)}$
$Land_{(t-1)}$	0.884***	0.922***	0.939***	0.870***	0.920***	0.917***
	(0.016)	(0.024)	(0.008)	(0.013)	(0.026)	(0.005)
Interest $Rate_{(t)}$	-0.890*	-0.317	-0.914***	-0.808*	-0.294	-0.777***
	(0.224)	(0.334)	(0.154)	(0.237)	(0.335)	(0.129)
Interest $Rate_{(t-1)}$	-2.004***	-1.659***	-1.732***	-2.035***	-1.666***	-1.803***
	(0.113)	(0.138)	(0.122)	(0.114)	(0.139)	(0.135)
Farm $Income_{(t)}$	0.175***	0.248***	0.095***	0.187***	0.258***	0.113***
	(0.016)	(0.029)	(0.016)	(0.017)	(0.031)	(0.022)
Farm $Income_{(t-1)}$	0.011	-0.133	0.053	0.020	-0.137	0.063
	(0.027)	(0.088)	(0.028)	(0.024)	(0.092)	(0.030)
Constant	2.112	1.561	7.010**	2.272	1.888	7.326**
	(1.311)	(2.066)	(1.852)	(1.389)	(2.035)	(2.022)
Obs.	159	212	265	165	220	275
R-squared	0.994	0.995	0.994	0.994	0.996	0.995
Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
LRM / k_{11}	24.95	25.33	43.38	21.87	24.50	31.08
LRM / k_{21}	1.60	1.47	2.43	1.59	1.51	2.12

Note: Robust standard errors are in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Additional robustness checks involved using farm loan rate from the Chicago Federal Reserve (regression results in appendix G) and the 10-year Treasury Constant Maturity Rate as the interest rate variable (regression results in appendix H). These two specifications had a high degree of similarity with the main ARDL model. The model that used the Chicago Federal Reserve farm loan rate as the main interest rate variable reported similar gross farm income effects on farmland values. When compared with the main ARDL model, the interest rate effects were stronger at time *t*, but immediately compensated by a weaker effect of lagged interest rates. Coefficients of lagged interest rates in the main model (federal funds rate as interest rate) were larger in magnitude than the ones in the model with the Chicago farm loan rate. Likewise, the model that utilized CMT-10 as the interest rate reported similar coefficients of gross farm income and lagged land values. Similar to the previous model, the stronger coefficient of interest rates at time t were compensated by weaker coefficients in *(t+1)*. In the long-run, however, there were no vast changes (except for the LRM for the interest rate effect in the Great Plains, which changes from 43.38 as reported in the main model to 76.92 in the CMT-10 model).

Arellano-Bond Estimation Methodology

The ARDL model in this study was assumed to be dynamically complete (Wooldridge, 2015), which means that the inclusion of lags for both the dependent and independent variables implied:

$$\text{(18)} \qquad E\left(Y_t \middle| X_{1t}, X_{2t}, Y_{t-1}, X_{1(t-1)}, X_{2(t-1)}, Y_{t-2} \ldots\right) = E\left(Y_t \middle| X_{1t}, X_{2t}, Y_{t-1}, X_{1(t-1)}, X_{2(t-1)}\right)$$

In other words, it is implied that as long as the first lags are controlled for, there is no need to control for further lags of either the dependent or the independent variables because no further lags affect the variable of interest (Wooldridge, 2015). It could be easily questioned whether one lag of the dependent and independent variables controlled for all the variables necessary to be included in the model. Although both AIC and BIC tests indicated that the model with one lag was more appropriate for the data, it may possibly help to include further lags by utilizing instrumental variables, which accounted for potential endogeneity concerns.

Arellano-Bond methodology (Arellano & Bond, 1991) is a well-known and common method to estimate dynamic panel datasets. Further lags of the dependent variable can be used as instrumental variables, and additional lags of the independent variables can be used to build an instrument matrix (Arellano & Bond, 1991). With the use of this matrix, one-step and two-step generalized method of moments estimators can be obtained (Arellano & Bond, 1991).

To ensure endogeneity concerns are addressed appropriately, a final important robustness check is performed where the models are derived using Arellano-Bond estimation methods (using the second and third lag of land values as instrumental variables to deal with endogeneity issues). The results are reported in Table 16.

There was a change in the magnitude of the interest rate coefficients for the I-States; and the interest rate effect at time t in the Arellano-Bond model was stronger and significant at the 99% confidence level (as opposed to its previous 90% confidence level). Compared to the main ARDL model, however, changes in magnitude of interest rate effects were not significantly different (especially for the lagged interest rate variable). Farm income effects were also consistent and similar to the ARDL model except that lagged farm incomes appeared negative and significant for I-States and Lakes regressions which is not suggested theoretically.

The most noticeable changes are the long-run multipliers, which nearly doubled (tripled) in the I-States and Lakes (Great Plains) regressions. Such large LRMs in the Arellano-Bond model were possibly driven by the fact that the error correction rates (the amount it takes land value to adjust to the changes in independent variables within the first year) are smaller in the Arellano-Bond model compared to the main ARDL model.

Table 16. Results w/ ARDL (first three columns) and Arellano-Bond (last three columns)

	I-States $Land_{(t)}$	Lakes $Land_{(t)}$	G.Plains $Land_{(t)}$	I-States $Land_{(t)}$	Lakes $Land_{(t)}$	G.Plains $Land_{(t)}$
$Land_{(t-1)}$	0.884***	0.922***	0.939***	0.962***	0.969***	0.966***
	(0.016)	(0.024)	(0.008)	(0.005)	(0.008)	(0.008)
Fed Funds $Rate_{(t)}$	-0.890*	-0.317	-0.914***	-1.081***	-0.265	-0.923***
	(0.224)	(0.334)	(0.154)	(0.179)	(0.327)	(0.122)
Fed Funds $Rate_{(t-1)}$	-2.004***	-1.659***	-1.732***	-1.928***	-1.615***	-1.663***
	(0.113)	(0.138)	(0.122)	(0.076)	(0.066)	(0.103)
Farm $Income_{(t)}$	0.175***	0.248***	0.095***	0.115***	0.270***	0.068***
	(0.016)	(0.029)	(0.016)	(0.010)	(0.036)	(0.020)
Farm $Income_{(t-1)}$	0.011	-0.133	0.053	-0.089***	-0.232***	-0.003
	(0.027)	(0.088)	(0.028)	(0.020)	(0.050)	(0.024)
Constant	2.112	1.561	7.010**	0.344	1.381	3.427***
	(1.311)	(2.066)	(1.852)	(0.411)	(1.481)	(0.866)
Obs.	159	212	265	159	212	265
R-squared	0.994	0.995	0.994	.z	.z	.z
Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
LRM / k_{11}	24.95	25.33	43.38	79.18	60.65	76.06
LRM / k_{21}	1.60	1.47	2.43	0.68	1.23	1.91

Note: Robust standard errors are in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

Limitations of Study

All economic models are built based on various underlying assumptions. One of the challenges often encountered when estimating a fixed effects model is the question of whether fixed effects are invariant across time. Although the Hausman test indicated that the fixed effects model was appropriate, exploring options that do not enforce strong assumptions to hold in a long-duration time series models is worthwhile.

The possibility of exploring other variable selection methods (i.e., machine learning techniques) must also be addressed, considering they have been proposed as alternatives to common forecasting statistical tools with time series data (Bonaccorso, 2018). Machine learning allows for dividing data into three important sets: (*a*) training; (*b*) validation; and (*c*) test data (Bonaccorso, 2018). The training data set is used to estimate a model and generally uses the majority of the data. The validation data set is used to run the selected model (the decision on a model is made based on its performance on the training data set). Lastly, the test data set is used to determine final model evaluation and uses data that have not been used in training (out-of-sample).

One common technique used for model selection is the k-fold cross validation method which involves division of data into k-subsets, training the data in a subset, and using the remainder of the subsets to evaluate the performance of the model (Rodríguez, Pérez, & Lozano, 2010). K-fold cross validation allows for the use of multiple subsets from the same data, and combination of the results of validation allows a final evaluation of the model's forecasting performance (Rodríguez et al., 2010). Two advantages of this methodology are bias reduction and individual testing of data points once they are used in training data sets (k-1) times.

The model may be improved if groups are assigned differently (perhaps on the basis of tonnage or value of agricultural crops produced). Furthermore, it may also be useful to develop state-level models that are specifically tailored to individual states, thereby altogether avoiding any type of grouping. Lastly, it is possible that natural climatic phenomena such as droughts or flooding (unaccounted for in this model) may influence farmland values and gross farm income, leading to over- or under-estimations.

Summary and Conclusions

Despite the challenges (such as serial correlation, heteroscedastic errors, and multicollinearity) in developing a model that is capable of predicting farmland values by using information on interest rate and farm income, the models developed in this study performed very well making predictions. On average, the I-States, Lakes, and Great Plains models predicted with an accuracy of 93.2%, 96.6%, and 91.7%, respectively. The R^2 of the models were quite high (≥ 0.994) indicating that the models captured causes of variation in the dependent variable extremely well. At time t when the change occurs, the I-States model indicated a 1% increase in interest rates would decrease farmland values by 0.89% while a 1% increase in gross farm income would increase farmland values by 0.18%. At the same period that the change occurs, the same interest rate shocks indicated a 0.32% (although insignificant) and 0.91% decrease in farmland values as a result of a 1% increase in interest rate level for the Lakes and the Great Plains regions, respectively; furthermore, a 1% increase in farm income increased farmland values by 0.25% and 0.10% in the same regions, respectively.

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CHAPTER 4. GENERAL CONCLUSIONS

Previous research on farmland values indicated that farmland values are affected by various factors; among the consistent variables to be included in the estimated models were interest rates and gross farm income (or variables that serve as proxy for farm income). In this study, three first-order autoregressive distributed lag models were generated that were capable of accurately predicting farmland value by using information on real interest rate levels and inflation-adjusted farmland values. The data on farmland values and gross farm income used in this study were transformed into logarithms to normalize the data and to control for variability across time periods. The models also controlled for heteroscedastic errors (by estimating robust standard errors), serial correlation (by including lagged farmland values into the model), and linear trends. In this study, short- and long-term effects induced by shocks of regressors on land values were generated.

The accuracy of predictions of farmland values using I-States, Lakes, and Great Plains models was, on average, 93.3%, 96.6%, and 91.7%, respectively. The models had significantly high R^2 (≥ 0.994) indicating that the models captured causes of variation in the dependent variable extremely well. The short-run effects were estimated by reporting the coefficients of the independent variables as estimated by the OLS regression. Therefore, at the time of the shock, the I-States and Great Plains models indicated that a 1% increase in interest rates would decrease farmland values by 0.89% and 0.91% in those regions, respectively (the Lakes model reported an insignificant interest rate variable at time t). On the other hand, the same models predicted that a 1%

increase in gross farm income would increase farmland values by 0.18%, 0.25%, and 0.10% in I-States, Lakes, and Great Plains regions, respectively. These results implied that the effects of interest rate changes are stronger than changes in gross farm income (which was also supported by previous findings). The long-term effects indicated that the number of lags necessary for the effect to dissipate half of the cumulative effect was at least six years (only half of the I-States interest rate effect was absorbed in five lags) and the maximum number of lags necessary to absorb half of the total effect was eleven years.

APPENDIX A. REGRESSION RESULTS W/ AND W/OUT LAGGED FARMLAND VALUES

Table 17: Statistical Results with (first three columns) and without (last three columns) Lagged Farmland Values as Regressor

	I-States $Land_{(t)}$	Lakes $Land_{(t)}$	G.Plains $Land_{(t)}$	I-States $Land_{(t)}$	Lakes $Land_{(t)}$	G.Plains $Land_{(t)}$
$Land_{(t-1)}$	0.884***	0.922***	0.939***			
	(0.016)	(0.024)	(0.008)			
Fed Funds $Rate_{(t)}$	-0.890*	-0.317	-0.914***	2.424**	1.229*	2.691**
	(0.224)	(0.334)	(0.154)	(0.329)	(0.513)	(0.688)
Fed Funds $Rate_{(t-1)}$	-2.004***	-1.659***	-1.732***	-4.074***	-2.935**	-4.115***
	(0.113)	(0.138)	(0.122)	(0.298)	(0.588)	(0.675)
Farm $Income_{(t)}$	0.175***	0.248***	0.095***	0.555***	0.644***	0.422***
	(0.016)	(0.029)	(0.016)	(0.044)	(0.075)	(0.063)
Farm $Income_{(t-1)}$	0.011	-0.133	0.053	0.712**	0.422*	0.658***
	(0.027)	(0.088)	(0.028)	(0.101)	(0.164)	(0.077)
Constant	2.112	1.561	7.010**	-20.659	-34.958**	-15.419
	(1.311)	(2.066)	(1.852)	(10.190)	(8.968)	(10.981)
Obs.	159	212	265	159	212	265
R-squared	0.994	0.995	0.994	0.956	0.963	0.939
Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Robust standard errors are in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX B. JOINT-SIGNIFICANCE OF BETA COEFFICIENTS TESTS

	I-States $Land_{(t)}$	Lakes $Land_{(t)}$	G.Plains $Land_{(t)}$
$Land_{(t-1)}$	0.884***	0.922***	0.939***
	(0.016)	(0.024)	(0.008)
Real Interest $Rate_{(t)}$	-0.890*	-0.317	-0.914***
	(0.224)	(0.334)	(0.154)
Real Interest $Rate_{(t-1)}$	-2.004***	-1.659***	-1.732***
	(0.113)	(0.138)	(0.122)
Farm $Income_{(t)}$	0.175***	0.248***	0.095***
	(0.016)	(0.029)	(0.016)
Farm $Income_{(t-1)}$	0.011	-0.133	0.053
	(0.027)	(0.088)	(0.028)
Constant	2.112	1.561	7.010**
	(1.311)	(2.066)	(1.852)
Obs.	159	212	265
R-squared	0.994	0.995	0.994

Note: Robust standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.10

Joint-Significance Tests

I-States Model:

Farm Income	
$H_0: \beta_{20} = \beta_{21} = 0$ H_A: negation Prob > F = 0.0091 Reject Null Hypothesis	Stata output: (1) farminc = 0 (2) farminc1 = 0 F(2, 2) = 108.93 Prob > F = 0.0091

Lakes Model:

Interest Rate		*Farm Income*	
$H_0: \beta_{10} = \beta_{11} = 0$ H_A: negation Prob > F = 0.0010 Reject Null Hypothesis	Stata output: (1) fedfundsr = 0 (2) fedfundsr1 = 0 F(2, 3) = 144.69 Prob > F = 0.0010	$H_0: \beta_{20} = \beta_{21} = 0$ H_A: negation Prob > F = 0.0003 Reject Null Hypothesis	Stata output: (1) farminc = 0 (2) farminc1 = 0 F(2, 3) = 339.96 Prob > F = 0.0003

Great Plains Model:

Farm Income	
$H_0: \beta_{20} = \beta_{21} = 0$ H_A: negation Prob > F = 0.0038 Reject Null Hypothesis	Stata output: (1) farminc = 0 (2) farminc1 = 0 F(2, 4) = 30.40 Prob > F = 0.0038

APPENDIX C. LONG-RUN EFFECTS AND MEDIAN LAG LENGTHS PROCEDURE

General Form for Long-Run Effects and Median Lag Lengths
(based on De Boef and Keele (2008), page 194)

At time t, or period (r=0), the effects equation is given by:

$$Y_t = \beta_{i0}$$

$$Y_t = \beta_{i0} X_{it}$$

Normalization of this effect as a proportion of the cumulative effect: $\frac{\beta_{i0}}{k_{i1}} = \tau_0$

At time (t+1), or period (r=1), the effects equation is given by:

$$Y_{t+1} = \alpha_1 Y_t + \beta_{i1} X_t = \alpha_1(\beta_{i0}) + \beta_{i1} = \rho_1$$

Normalization of this effect as a proportion of the cumulative effect: $\frac{\rho_1}{k_{i1}} = \tau_1$

At time (t+2), or period (r=2), the effects equation is given by:

$$Y_{t+2} = \alpha_1 Y_{t+1} = \alpha_1(\rho_1) = \rho_2$$

the formula incorporates no additional short-term effects of X_t

Normalization of this effect as a proportion of the cumulative effect: $\frac{\rho_2}{k_{i1}} = \tau_2$

At time (t+3), or period (r=3), the effects equation is given by:

$$Y_{t+3} = \alpha_1 Y_{t+2} = \alpha_1(\rho_2) = \rho_3$$

the formula incorporates no additional short-term effects of X_t

Normalization of this effect as a proportion of the cumulative effect: $\frac{\rho_3}{k_{i1}} = \tau_3$

…

The same procedure continues until the sum of the normalized/standardized effects (τ_i) or m, equals or exceeds 0.5 (find median lag length).

APPENDIX D. WITHIN-SAMPLE ESTIMATION SUMMARY STATISTICS

The model is run from 1963 to 2016. Farmland values are predicted from 1963 to 2016 (within-sample). The within-sample farmland value predictions are summarized below.

Table 17. Descriptive Statistics for Within-Sample Estimations (I-States)

Variable	Obs	Mean	Std.Dev.	Min	Max
Within-Sample Predictions	159	7.36	249.73	-569.74	1781.67

Table 18. Descriptive Statistics for Within-Sample Estimations (Lakes)

Variable	Obs	Mean	Std.Dev.	Min	Max
Within-Sample Predictions	212	-2.32	142.08	-419.35	620.79

Table 19. Descriptive Statistics for Within-Sample Estimations (Great Plains)

Variable	Obs	Mean	Std.Dev.	Min	Max
Within-Sample Predictions	265	-0.10	75.07	-323.21	553.62

APPENDIX E. SUMMARY OF FORECAST ERRORS WITH 1962-2017 ARDL

Table 20. Descriptive Statistics for the Forecast Errors: 1962-2015 and 1963-2017 models (I-States)

Variable	Obs	Mean	Std.Dev.	Min	Max
1963-2015	159	20.69	271.19	-569.74	1781.67
1963-2017	165	11.51	280.29	-634.40	1789.87

Table 21. Descriptive Statistics for the Forecast Errors: 1962-2015 and 1963-2017 models (Lakes)

Variable	Obs	Mean	Std.Dev.	Min	Max
1963-2015	212	-7.52	151.17	-484.71	651.51
1963-2017	220	-1.63	146.90	-433.22	612.79

Table 22. Descriptive Statistics for the Forecast Errors: 1962-2015 and 1963-2017 models (G. Plains)

Variable	Obs	Mean	Std.Dev.	Min	Max
1963-2015	265	6.53	87.38	-323.21	553.62
1963-2017	275	0.29	90.42	-367.63	529.49

APPENDIX F. PREDICTIONS BETWEEN 1962-2015 AND 1962-2017 ARDL

Table 23. Differences between Predicted and Actual Farmland Values for 2016 and 2017 (I-States)

State	Year	Difference 1962-2015	Difference 1962-2017
Illinois	2016	314.00	220.78
Illinois	2017	433.70	342.47
Indiana	2016	-337.31	-475.18
Indiana	2017	-90.81	-231.50
Iowa	2016	1030.07	1008.05
Iowa	2017	894.40	866.39

Table 24. Differences between Predicted and Actual Farmland Values for 2016 and 2017 (Lakes)

State	Year	Difference 1962-2015	Difference 1962-2017
Ohio	2016	-24.04	-30.31
Ohio	2017	116.42	145.51
Michigan	2016	-16.18	-22.21
Michigan	2017	-15.79	-2.45
Minnesota	2016	410.78	367.05
Minnesota	2017	464.30	450.38
Wisconsin	2016	107.75	92.03
Wisconsin	2017	-179.60	-168.34

Table 25. Differences between Predicted and Actual Farmland Values for 2016 and 2017 (G.Plains)

State	Year	Difference 1962-2015	Difference 1962-2017
Missouri	2016	-73.84	-186.26
Missouri	2017	85.26	-28.94
Kansas	2016	339.97	316.39
Kansas	2017	238.37	218.67
Nebraska	2016	456.14	418.56
Nebraska	2017	434.29	397.63
North Dakota	2016	101.93	52.59
North Dakota	2017	29.02	-17.24
South Dakota	2016	92.93	30.10
South Dakota	2017	119.40	57.72

APPENDIX G. ROBUSTNESS CHECK WITH CHICAGO FED FARM LOAN RATE

Table 19: Statistical Results with Chicago Federal Reserve Farm Loan Rate

	I-States Land$_{(t)}$	Lakes Land$_{(t)}$	G.Plains Land$_{(t)}$	I-States Land$_{(t)}$	Lakes Land$_{(t)}$	G.Plains Land$_{(t)}$
Land$_{(t-1)}$	0.884***	0.922***	0.939***	0.897***	0.929***	0.947***
	(0.016)	(0.024)	(0.008)	(0.013)	(0.014)	(0.009)
Fed Funds Rate$_{(t)}$	-0.890*	-0.317	-0.914***			
	(0.224)	(0.334)	(0.154)			
Fed Funds Rate$_{(t-1)}$	-2.004***	-1.659***	-1.732***			
	(0.113)	(0.138)	(0.122)			
Farm Income$_{(t)}$	0.175***	0.248***	0.095***	0.131**	0.174***	0.105**
	(0.016)	(0.029)	(0.016)	(0.027)	(0.028)	(0.028)
Farm Income$_{(t-1)}$	0.011	-0.133	0.053	0.010	-0.114	0.056
	(0.027)	(0.088)	(0.028)	(0.016)	(0.061)	(0.031)
Chicago FLR$_{(t)}$				-1.612***	-0.919*	-1.518***
				(0.109)	(0.327)	(0.081)
Chicago FLR$_{(t-1)}$				-1.300***	-1.286**	-1.249***
				(0.118)	(0.317)	(0.247)
Constant	2.112	1.561	7.010**	-3.041**	-2.975	4.159
	(1.311)	(2.066)	(1.852)	(0.698)	(1.446)	(1.953)
Obs.	159	212	265	135	180	225
R-squared	0.994	0.995	0.994	0.991	0.993	0.992
Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
LRM / k_{11}	24.95	25.33	43.38	28.27	31.06	52.21
LRM / k_{21}	1.60	1.47	2.43	1.37	0.85	3.04

Note: Robust standard errors are in parenthesis.
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX H. ROBUSTNESS CHECK WITH CMT-10

Table 18: Statistical Results with CMT-10 (last three columns)

	I-States Land$_{(t)}$	Lakes Land$_{(t)}$	G.Plains Land$_{(t)}$	I-States Land$_{(t)}$	Lakes Land$_{(t)}$	G.Plains Land$_{(t)}$
Land$_{(t-1)}$	0.884***	0.922***	0.939***	0.886***	0.923***	0.961***
	(0.016)	(0.024)	(0.008)	(0.007)	(0.016)	(0.010)
Fed Funds Rate$_{(t)}$	-0.890*	-0.317	-0.914***			
	(0.224)	(0.334)	(0.154)			
Fed Funds Rate$_{(t-1)}$	-2.004***	-1.659***	-1.732***			
	(0.113)	(0.138)	(0.122)			
Farm Income$_{(t)}$	0.175***	0.248***	0.095***	0.142**	0.184***	0.060**
	(0.016)	(0.029)	(0.016)	(0.017)	(0.026)	(0.015)
Farm Income$_{(t-1)}$	0.011	-0.133	0.053	0.017	-0.083	0.041
	(0.027)	(0.088)	(0.028)	(0.009)	(0.060)	(0.031)
Real CMT-10$_{(t)}$				-1.858***	-1.175**	-1.811***
				(0.119)	(0.347)	(0.087)
Real CMT-10$_{(t-1)}$				-1.201**	-1.228*	-1.189***
				(0.183)	(0.395)	(0.243)
Constant	2.112	1.561	7.010**	-1.606	-0.795	3.458*
	(1.311)	(2.066)	(1.852)	(0.689)	(1.190)	(1.409)
Obs.	159	212	265	159	212	265
R-squared	0.994	0.995	0.994	0.995	0.996	0.996
Linear Trend	Yes	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Robust SE	Yes	Yes	Yes	Yes	Yes	Yes
LRM / k_{11}	24.95	25.33	43.38	26.83	31.21	76.92
LRM / k_{21}	1.60	1.47	2.43	1.39	1.31	2.59

Note: Robust standard errors are in parenthesis
*** p<0.01, ** p<0.05, * p<0.1

APPENDIX I. DESCRIPTIVE STATISTICS FOR I-STATES, LAKES, AND GREAT PLAINS

Table 26. Descriptive Statistics for I-States Region

Variable	Obs	Mean	Std.Dev.	Min	Max
Land (log)	168	7.30	.93	5.53	9.05
Farm Income (log)	168	15.84	.73	14.08	17.40
Real Federal Funds Rate	168	.01	.02	-.03	.06

Table 27. Descriptive Statistics for Lakes Region

Variable	Obs	Mean	Std.Dev.	Min	Max
Land (log)	224	7.00	1.00	4.96	8.66
Farm Income (log)	224	15.38	.75	13.719	16.99
Real Federal Funds Rate	224	.01	.02	-.03	.06

Table 28. Descriptive Statistics for Great Plains Region

Variable	Obs	Mean	Std.Dev.	Min	Max
Land (log)	280	6.12	.98	4.01	8.13
Farm Income (log)	280	15.39	.83	13.49	17.11
Real Federal Funds Rate	280	.01	.02	-.03	.06