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Do Profitable Farms Remain Profitable? Transition Probabilities Using Markov Switching Models Applied to Kansas Farm Data

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ABSTRACT

Financial vulnerability has been observed across agricultural production regions; however, uncertainty regarding farms' persistence within specific profitability categories exists. This study compared farm characteristics that persist in most and least profitable categories and then evaluated the probability that farms transitioned among profitability categories. Using 425 Kansas Farm Management Association (KFMA) farms that were present for the 20-year period 1994–2013, the persistence of remaining or transitioning to another profitability category was tested. Specifically, Markov transition probabilities were estimated for Kansas and the six regional KFMA regions. Comparisons of farms that persist in the highest and lowest profitability categories revealed no dramatic differences in acreage or other physical characteristics. Kansas farms tend to persist in their current profitability category, suggesting that operator skill and/or quality of farmland dominate random factors. In general, transition probabilities were greater for the highest and lowest profitability categories than for the middle categories. Farms were observed switching from highest to lowest profitability categories between 5% and 20% of the time within one year. Farmers were likely to stay in the highest profitability group more than half the time. By contrast, farmers were likely to stay in the lowest profitability group 42% of the time. Just like with the most profitable group, the least profitable group has a greater likelihood of remaining at the bottom, indicating that random events do not cause persistence.

KEYWORD

farm profitability, Markov, transition probability, persistence

INTRODUCTION

The primary goal of this paper was to utilize the properties of Markov probabilities to provide insight into farm profitability persistence. The value of the objective lies within the transition probabilities and the interpretation of said probabilities. If the highest-ranked farms persistently remained in their initial category, this would imply that controllable management factors were at work. However, if the transition probabilities showed that farms freely entered and exited categories, then perhaps the profitability of a farm was dependent upon uncontrollable factors. These assumptions could lead to identification of characteristics that would provide important information to the agricultural industry.

Farms strive to maintain or improve their financial positions in the presence of controllable (seed genetics, nutrient management, chemical application, marketing) and uncontrollable (weather, soil properties, geopolitical, economical) factors. Many of the controllable factors can be attributed to management, while many of the uncontrollable factors can be attributed to farm location and an additional catchall of luck. Despite the large impact of uncontrollable factors, certain farms have been shown to consistently outperform their peers. Farms that are more profitable relative to their peers have a greater likelihood of succeeding in the long run. These farms typically have a greater probability of earning a profit in bad years and will enjoy greater income in good years. By contrast, farms that are less profitable relative to their peers have a greater likelihood of becoming insolvent. These farms are less likely to earn a profit and in a bad year could lose enough to exhaust their equity. Important question are whether a farm can improve or maintain its profitability ranking compared to other farms and what the probabilities are that farms may switch to another profitability ranking. In order to determine the probabilities of Kansas farms maintaining or transitioning to another category, net farm income (NFI) data was gathered from the Kansas Farm Management Association (KFMA). The probability of transitioning between profitability ranks is important so that farmers and their financial advisers understand how quickly farms can switch from financial security to vulnerability.

When the probability that a farm remains in its current profitability ranking is higher than the probability that it switches to another profitability ranking, it is said to be persistent. If farm profitability is based on random luck, then farms will freely transition between profitability categories just as often as remaining in the current profitability category. Persistence is a desirable characteristic when a farm is in one of the higher profitability categories and can be interpreted as the farm being managed with above-average skills.

BACKGROUND AND LITERATURE REVIEW

Over the past decade NFI has steadily risen, peaking in 2013 at over $120 billion (Key, Prager, & Burns, 2017). This in turn has led many producers to increase their production acreage by making sizable investments in long-term assets such as land, thereby generating greater financial exposure. This trend in land acquisitions has driven land prices to all-time highs, making it appear to be a solid asset on farmers' balance sheets, but the signs of a land bubble are evident. According to Burns, Tullman, and Harris (2015), a financial environment similar to the 1980s farm crisis could potentially arise under a specific set of conditions. They cite falling land prices in 2014 coupled with lower commodity prices along with smaller NFIs as potential sources of distress. Although a crisis could arise, the current U.S. Department of Agriculture (USDA) report indicated that estimates for farm debt to equity and debt to asset ratios would continue to decrease, allowing farms to maintain financial stability (Park et al., 2010). Additionally, lower interest rates and stronger debt management skills have prevented another farm crisis.

Despite the expected stability reported by Park et al. (2010), recent changes in financial risk that farmers are exposed to have brought about uncertainty. The USDA forecast for NFI in 2016 is predicted to decline. This will continue the decline in farm profitability beginning in 2014 (Key et al., 2017). Consequently, considerable interest has been exhibited to identify farms with above-average managerial performances; however, identifying and quantifying managerial performances provides a unique set of problems. Sonka, Hornbaker, and Hudson (1989) attempted to identify proxies for managerial variables using statistical analyses of Illinois farm data from the period 1976–1983. Ford and Shonkwiler (1994) used maximum likelihood estimators to find variables of interest and confirmatory factor analysis. Goodwin, Featherstone, and Zeuli (2002) used Kansas farm data with two goals in mind: (1) determining the roles that experience and learning play in determining yield performance and (2) quantifying the magnitude of these variables of interest and their impact on yield performance. Yeager and Langemeier (2011) applied nonparametric data analysis to Kansas farm data while focusing on operator age and its relationship to technical efficiency and looking for the convergence or divergence of farm performances over time. Research by Mishra, Wilson, and Williams (2009) utilized returns on assets as a measure of managerial performance with a focus on farm operator characteristics, farm production and marketing efficiency, and other management techniques. Zech and Pederson (2003) utilized regression analysis to find characteristics linked to loan repayment ability while comparing their results to previous studies with a logit model. Many different approaches exist when trying to explain farm management's impact on farm success. The identification of managerial variables and their impacts from these above-mentioned research articles lend themselves to this research. One of the first metrics useful in evaluating farm management performance is the persistence with which farm businesses remain profitable.

Farm profitability persistence has been evaluated in Illinois (Kuethe, Paulson, & Schnitkey, 2015; Li & Paulson, 2014; Urcola et al., 2004) and Kansas (Herbel & Langemeier, 2012; Ibendahl, 2013). Urcola et al. (2004) focused on agronomic yield rather than profitability. Urcola et al. (2004) and Ibendahl (2013) evaluated management skill versus stochastic process under the guise of luck. These previous studies of farm management association records programs can be considered comparative analyses, comparing and contrasting characteristics of the most and least profitability groups. Li and Paulson (2014) continued the use of Illinois data by expanding the time horizon of Urcola et al. (2004) and correcting for survivor bias. In Kansas, Langemeier and DeLano (1999) applied data envelopment analysis to a 24-year panel from the KFMA databank. Ibendahl (2013) expanded upon the Kansas study by evaluating farms allocated to decile groups based on profitability. A different approach from Nivens, Kastens, and Dhuyvetter (2002) investigated how a farm varied from the average observation in the following categories: profit, input cost, yield, crop price, technology adoption, seeding rates, farm size, government payments, and risk. They reported that input costs, yield, and seeding rates had the largest impact on farm profitability. Given the comparisons between most and least profitability states, the next logical question to address is the probability of farms transitioning between profitability states or remaining in their current state. An exhaustive review of the literature revealed no studies estimating the transition probabilities with respect to persistence or movement between profitability states; however, Kuethe et al. (2015) evaluated the persistence with respect to a definition of financial vulnerability from the Economic Research Service that focused on farm's debt to asset ratios and NFI.

The probability of remaining in the highest (lowest) profitability state can be estimated using ranks across multiple years. Superficially, Markov chain transition probabilities (Eddy, 1998) that have been applied to soil erosion classification (Skaggs & Ghosh, 1999), livestock farm size (Gillespie & Fulton, 2001), health and medicine (Jung, 2006), and land-use changes (Muller & Middleton, 1994) will be applied to Kansas farm profitability data.

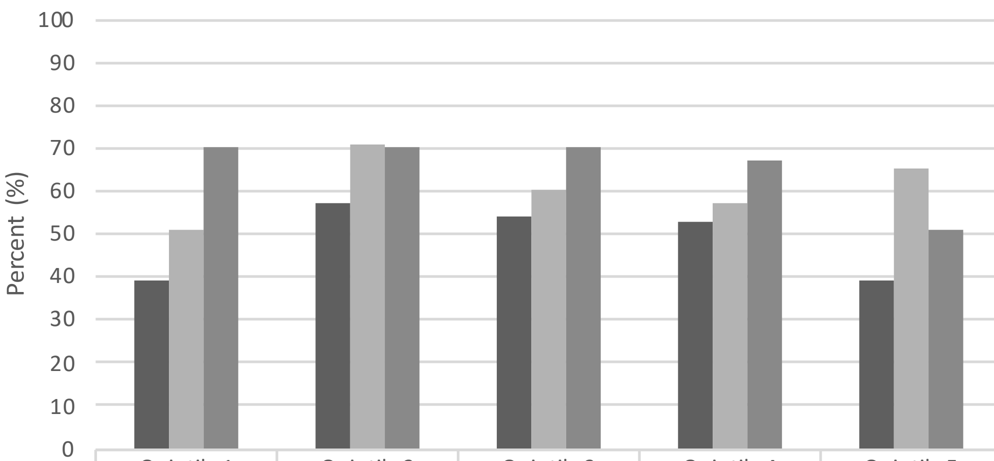
DATA AND METHODS

Persistence was tested on the 425 farms present in the KFMA data set for all years from 1994 through 2013. The KFMA databank is suitable for estimating transition probabilities due to the ample number of farms. Even when considering only farms that existed for all 20 years in the database, there were 425 farms available for analysis. For perspective, KFMA farm type was determined by the percentage of labor dedicated to a specific production type, which leads to over 40 different farm classification types. In our sample the majority of farms were considered grain farms.

For each year, farms were ranked in order of per acre NFI and then evenly assigned to one of five states of the world based on profitability such that each state contained 20% of all farms. The NFI per acre metric was used to indicate persistence because it removes bias caused by farm size. This does create concerns for unpaid family and operator labor that could skew results. It should be noted that Kansas farms in the top quintile on average had 1.26 unpaid farm operators; however, unpaid operators have been steadily decreasing from a high of 1.35 in 1994 to a low of 1.08 in 2013, showing that farm management structure among the top farms is becoming more consolidated. Additionally, the top-performing farms have a greater unpaid operator amount, with an average of $32,646.11. Regional differences in the farm management structure and the potential for larger farms to have dedicated operators with defined compensation rates will require further analysis of the KFMA data.

The quintiles were named Quintile 1 through Quintile 5. Quintile 1 contains the top 20% of farms with respect to the highest per acre NFI, farms with 20th to 40th percentile per acre NFI were assigned to Quintile 2, and so on, with the lowest 20% per acre NFI farms assigned to Quintile 5. All farms were reassigned each year based on per acre NFI rankings; therefore, a given farm may change from any one quintile to any other quintile from year to year. Only farms that were in the data set for the entire 20-year time frame were used for the analysis.

In all five quintiles at least 50% or more of the farms were considered grain production farms. Figure 1 shows the proportion of farms that could be considered grain farms and how those proportions changed over time. Figure 1 indicates that Kansas farms have been increasing specialization over time; however, it should be noted that farms in the lowest rank failed to hold the same trend. Crop labor percentages were similar across quintiles but significantly different between Quintile 1 and Quintile 5 (p-value = 0.002). This may suggest that focusing on a single area of production may improve farm persistence.



	Quintile 1	Quintile 2	Quintile 3	Quintile 4	Quintile 5
1994	39	57	54	53	39
2004	51	71	60	57	65
2013	70	70	70	67	51

Figure 1. **Proportion of grain farms in KFMA 1994–2013**

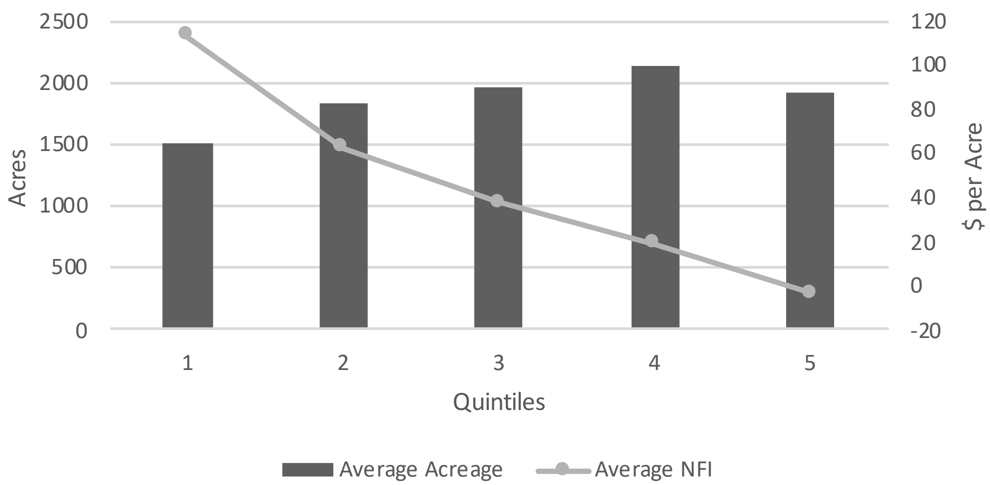


Figure 2. **KFMA farm size and profitability distribution by quintile**

Over the time span, the average farm size ranged from 1,502 acres for Quintile 1 to 2,129 acres for Quintile 4. The average farm size increased from Quintile 1 to Quintile 4; however, Quintile 5 was smaller than Quintile 4, suggesting that economies of scale have not played a role. Average farm acreage was statistically smaller for Quintile 1 than Quintile 5 (p-value = 0.009). As can be seen in Figure 2, despite the return to smaller acreage in Quintile 5, the average median per acre NFI is still negative, suggesting that the poorest performing farms are likely the result of management, not size. NFI was statistically significantly lower in Quintile 5 than in Quintile 1 (p-value < 0.0001).

Farms that remained in the top and bottom quintiles for 10 or more years were evaluated separately. Sixty-three farms were in Quintile 1 for at least 10 years. Fifty-one farms were in Quintile 5 for at least 10 years. Characteristics of these persistent farms were tested to determine if they were statistically significant during the most recent year. The farms that remained in Quintile 1 had similar farm size (p-value > 0.3); however, crop labor percentages and NFI per acre were higher (p-value < 0.01 for both). Farms that persisted in

Table 1. Farms remaining in Quintile 1 for more than 10 years

	Acres	Crop Labor	NFI/Acre
10th percentile	510	0.40	16
Mean	1721	0.82	153
Median	1363	0.94	134
90th percentile	3720	1.00	345

Table 2. Farms remaining in Quintile 5 for more than 10 years

	Acres	Crop Labor	NFI/Acre
10th percentile	370	0.26	–18
Mean	1646	0.66	24
Median	1125	0.68	16
90th percentile	3409	1.00	69

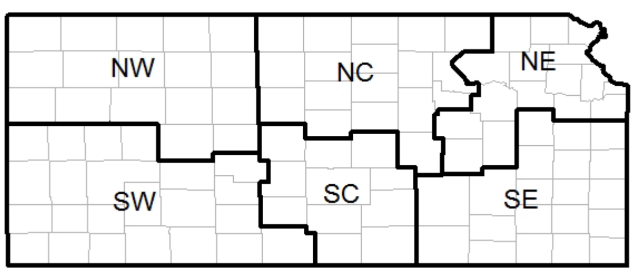


Figure 3. Map of KFMA regions within Kansas

both Quintile 1 (Table 1) and Quintile 5 (Table 2) were of similar size, at approximately 1,700 acres. Farms with a higher percentage of labor devoted to crops tended to persist in the more profitable group (see Table 1).

The data was also broken into subsets for each of the six KFMA regions (Figure 3). Each KFMA region differed by number of farms, ranging from a high of 165 in the southeastern region to a low of 18 in the northwestern region. Figure 4 presents the number of farms for each KFMA region.

Accrual per acre annual NFI was calculated for each farm for each of the 20 years. KFMA farms calculate NFI using accrual accounting and also use management depreciation instead of tax depreciation. The management depreciation is an attempt to match depreciation to the actual decline in asset value. Management depreciation lowers the asset value slower than would tax depreciation.

The probability of transitioning from one quintile to any other quintile was estimated using the 1994–2013 KFMA data set. Each year the percentage of farms that stayed in the same quintile or moved to another was calculated. Therefore, each of the 425 farms contributed 19 observations over the 20-year period. An ergodic first-order Markov chain was utilized to build the transition matrix. From this, probabilities were calculated and indicated that in any given year a farm would stay in the same profitability quintile or change to a different quintile. A one-step transition probability

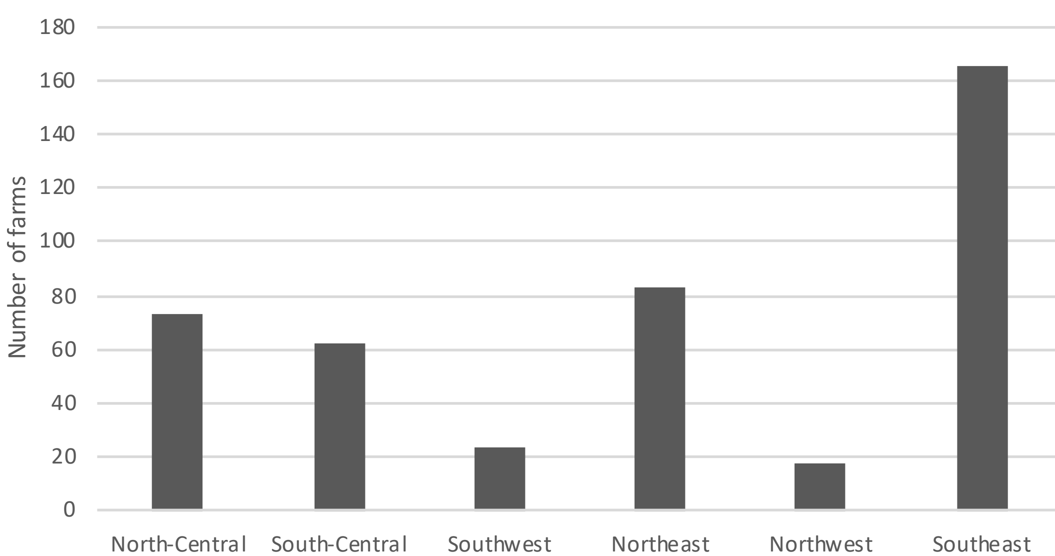


Figure 4. Number of farms by KFMA region

matrix, P, from one profitability state to another profitability state was estimated. The transition probability matrix, P, is the matrix consisting of one-step transition probabilities, p_{ij}, defined as

$$p_{ij} = \Pr\{X_t = j \mid X_{t-1} = i\} \quad (1)$$

where p_{ij} represents one-step transition probabilities equal to the probability of being in profitability state *j*, given that the individual farm was in profitability state *i* in previous year $t-1$. The underlying assumption of Markov chain models is that the state of the world today (time *t*) is only a function of the previous time period (time $t-1$).

Markov transition stability or the probability of a farm remaining in a given profitability state is referred to as persistence. The probability of transitioning from one state to any other state was estimated for all farms that were in the KFMA database for all years from 1994 to 2013.

RESULTS

Of the 425 farms in the databank, 289 or nearly two-thirds were ranked in Quintile 1 at least once (Table 3). Substantially more farms were ranked in the lowest four quintiles at least once. The highest-frequency quintile was Quintile 3, with 390 or 92% of farms entering that rank at least once. Two farms remained in Quintile 1 for all 20 years. The most number of times a given farm was in Quintiles 2, 3, or 4 was 13 or 14, substantially fewer than the number of farms that remained in Quintiles 1 and 5. Two farms remained in Quintile 5 for 19 years of the 20-year period, indicating that the worst-performing farms were persistent. Although fewer farms persistently visited Quintiles 1 and 5, at least a few farms remained in these top and bottom profitability categories longer than in the middle three quintiles. However, a farm with better than average soils or in a region with higher annual rainfall amounts could also show persistence in the higher profitability categories relative to other farms. Conversely, persistence in the lower profitability categories is not a desirable characteristic and can be attributed to poor farm management, poor soils, or annual rainfall that is less than adequate. The lack of persistence across all profitability categories indicates factors outside the control of the farmer.

The transition probabilities for all 425 KFMA farms ranked across quintiles are presented in Table 4 and are graphically represented in Figure 5. The values on the principal diagonal indicate the probability that farms will remain in their current quintile, p_{ii}, with other values indicating the likelihood of them transitioning into a different quintile, p_{ij}. For example, farms initially in Quintile 1 are likely to remain in Quintile 1 about half the time (probability equal to 0.52). Similarly, farms in Quintile 5 have a moderate chance (probability = 0.42) of remaining in the lowest profitability category. There is a slight chance (probability = 0.09) that a farm in Quintile 1 in a given year can transition to Quintile 5 the next year. Likewise, there is a similar chance (probability = 0.07) that a farm can transition from Quintile 5 to Quintile 1 within one year. Figure 5 graphically represents the state transition for the five states. The arrows from each quintile to other quintiles indicate the transition probably, $p_{ij.}$

The highest values in each row indicate whether farms are likely to remain in their current quintile

Table 3. Distribution of 425 KFMA farms by quintiles, 1994 to 2013

	Number of Farms Visiting Quintile at Least Once	Maximum Number of Times an Individual Farm Visits Quintile
Quintile 1	289	20
Quintile 2	360	13
Quintile 3	390	14
Quintile 4	383	14
Quintile 5	352	19

Table 4. NFI ranked by quintile transition probabilities, all KFMA regions, N = 425

	1	2	3	4	5
1	**0.52**	0.20	0.12	0.08	0.09
2	0.23	**0.29**	0.22	0.16	0.11
3	0.11	0.23	**0.27**	0.24	0.16
4	0.07	0.15	0.24	**0.30**	0.24
5	0.07	0.12	0.16	0.23	**0.42**

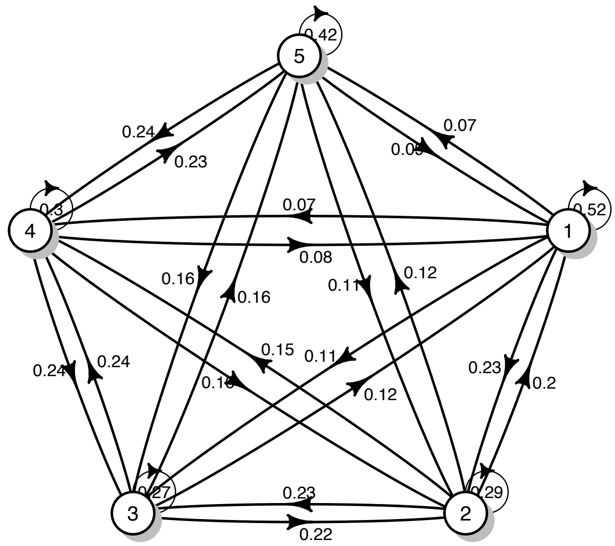


Figure 5. **Probability network graph, NFI ranked by quintile transition probabilities, all KFMA regions, *N* = 425**

rather than switching to another quintile (highest probability in boldface for emphasis). When the highest value in each row corresponds to values along the principal diagonal from upper left to lower right (i.e., the probability of beginning in and remaining in the same quintile), then persistence is expected. When the highest values in each row are not along the principal diagonal, then persistence is not expected and can be considered unstable. Even when transition probabilities are persistent, an individual farm may transition from any quintile to any other quintile from one year to the next, as signified by the absence of zeros in the transition probability tables.

In Table 4, it should be noted that the second- and third-highest transition probabilities are immediately next to the principal diagonal, indicating that when farms switch between profitability categories they are likely to transition one quintile higher or lower rather than jump across multiple profitability categories.

When considering only the farms located within individual KFMA regions some similarities and differences exist compared to Kansas-level results. These relationships varied between different regions in Kansas, as shown by the six different KFMA regions in Tables 3 through 8. Similar to the Kansas-level results, farms in the north-central KFMA region were persistent with respect to their tendency of remaining in their current quintile (Table 5). Farms in the highest and lowest profitability categories are more likely to remain in the current quintile than in the middle three quintiles. As with the Kansas-level results, farms in the north-central KFMA region can transition from Quintile 1 to the Quintile 5 in one year (probability = 0.07).

The south-central KFMA region differed from the Kansas-level results in that the transition probabilities along the principal diagonal were not the highest in each row (Table 6). Although farms in the highest and lowest quintiles were likely to remain in the current quintile, the remaining quintiles did not have the expected persistence. The transition probabilities of switching from Quintile 1 to Quintile 5 (probability = 0.06) were similar to Kansas-level results.

The southwest KFMA region also differed from Kansas-level results (Table 7). The highest and lowest profitability categories were persistent, while the remaining three profitability categories were unstable. The probabilities of transitioning from Quintile 1 to Quintile 5 (probability = 0.20) and Quintile 5 to Quintile 1 (probability = 0.23) were much higher than Kansas-level results.

The northeast KFMA region results were similar to Kansas-level results (Table 8). The transition probabilities indicate persistence. The probability

Table 5. **NFI ranked by quintile transition probabilities, North-Central KFMA region, *N* = 73**

	1	2	3	4	5
1	**0.50**	0.21	0.12	0.10	0.07
2	0.21	**0.27**	0.24	0.17	0.12
3	0.13	0.22	**0.29**	0.24	0.11
4	0.09	0.16	0.19	**0.29**	0.26
5	0.06	0.13	0.13	0.23	**0.45**

Table 6. **NFI ranked by quintile transition probabilities, south-central KFMA region, *N* = 62**

	1	2	3	4	5
1	**0.61**	0.20	0.09	0.04	0.06
2	0.21	0.23	**0.26**	0.15	0.15
3	0.10	**0.35**	0.10	0.25	0.21
4	0.12	0.12	0.14	**0.27**	**0.35**
5	0.06	0.08	0.18	0.25	**0.42**

Table 7. NFI ranked by quintile transition probabilities, southwest KFMA region, *N* = 24

	1	2	3	4	5
1	**0.38**	0.15	0.11	0.16	0.20
2	0.22	0.21	0.19	0.24	0.14
3	0.23	**0.25**	**0.24**	0.14	0.14
4	0.13	0.15	0.22	0.21	**0.29**
5	0.23	0.12	0.14	**0.25**	**0.26**

Table 8. NFI ranked by quintile transition probabilities, northeast KFMA region, *N* = 83

	1	2	3	4	5
1	**0.50**	0.22	0.11	0.07	0.11
2	0.21	**0.31**	0.25	0.13	0.10
3	0.13	0.20	**0.28**	0.26	0.13
4	0.07	0.14	0.21	**0.34**	0.24
5	0.09	0.11	0.15	0.21	**0.44**

Table 9. NFI ranked by quintile transition probabilities, northwest KFMA region, *N* = 18

	1	2	3	4	5
1	**0.43**	0.17	0.09	0.12	0.19
2	0.21	**0.32**	0.21	0.17	0.10
3	0.12	0.15	**0.32**	0.18	0.22
4	0.13	0.17	0.20	**0.32**	0.17
5	0.19	0.11	0.13	0.23	**0.34**

of transitioning from Quintile 1 to Quintile 5 (probability = 0.11) was slightly higher than the Kansas-level probabilities.

The northwest KFMA region has the fewest number of observations of all regions (*N* = 18); however, the transition probabilities indicate persistence (Table 9). Unlike Kansas-level results, the second- and third-highest transition probabilities were not adjacent to the principal diagonal. The probability of transitioning from Quintile 1 to Quintile 5 (probability = 0.19) or Quintile 5 to Quintile 1 (probability = 0.19) were nearly 20%, about twice as high as for the Kansas-level results.

The transition probabilities for the southeast KFMA region were similar to the Kansas-level results (Table 10). Transition probability indicated persistence. The probability of transitioning from Quintile 1 to Quintile 5 (probability = 0.07) or Quintile 5 to Quintile 1 (probability = 0.06) were similar to Kansas-level results.

Table 10. NFI ranked by quintile transition probabilities, southeast KFMA region, *N* = 165

	1	2	3	4	5
1	**0.55**	0.22	0.10	0.06	0.07
2	0.23	**0.29**	0.22	0.14	0.12
3	0.10	0.22	**0.30**	0.22	0.16
4	0.07	0.12	0.22	**0.34**	0.25
5	0.06	0.13	0.16	0.23	**0.43**

SUMMARY AND CONCLUSIONS

A 20-year KFMA data set was used to estimate transition probabilities between five NFI quintiles. Results indicated that farms tend to persist in their current profitability category, suggesting that operator skill and/or quality of farmland dominate random factors. In general, the transition probabilities were greater for the highest and lowest profitability categories than for the three middle quintiles. That being said, switching from the highest probability categories to the lowest profitability categories still occurred between 5% and 20% of the time within one year.

By contrast, farmers were likely to stay in the lowest profitability group 42% of the time, which is the second-highest probability of staying within the same profit category. This result is not positive for farmers, as they do not want to be in the least profitable group. Farms within the least profitable group are losing the most money each year (or at least earning the smallest profits). These farms are likely to be the most vulnerable to financial problems, and remaining in the least profitable group year after year increases the probability that these farms could become insolvent.

As is the case for the most profitable group, the least profitable group has a greater likelihood of remaining in this bottom group. Again, this could be an indication that more than just random events are causing the persistence. Whether the reason is poor management or perhaps location-specific items such as poor soils, inadequate rainfall, etc., remains to be determined, but the interrank transition probabilities of Quintiles 2, 3, and 4 suggest that management, more so than farm location, has an impact.

Southwest and south-central KFMA regions did not exhibit strong persistence compared to the remaining four KFMA regions and Kansas-level results. In addition, persistence was indicated by the transition probabilities especially among the largest sample sizes. Persistence was not evident in south-central and southwest KFMA regions potentially due to the smaller number of farms and the prevalence of diversified enterprises. Given the risk management aspect of diversification, it was expected that farms with both crops and livestock production would not persist at the top profitability ranking and instead frequently switch between quintiles.

REFERENCES

Burns, C., Tullman, S., & Harris, J. (2015, July). Farm financial stress in a changing economic environment: Simulating credit risk with new imputed ARMS data on farm debt. Paper presented at the Applied Economics Association and Western Agricultural Economics Association Annual Meeting San Francisco, California. July 26–28.

Eddy, S. R. (1998). Profile hidden Markov models. *Bioinformatics Review, 14*(9), 755–763.

Ford, S., & Shonkwiler, J. (1994). The effect of managerial ability on financial success. *Agricultural Resource and Economics Review, 23*(2), 150–157.

Gillespie, J. M., & Fulton, J. R. (2001). A Markov chain analysis of the size of hog production firms in the United States. *Agribusiness*, *17*(4), 557–570.

Goodwin, B., Featherstone, A., & Zeuli, K. (2002). Producer experience, learning by doing, and yield performance. *American Journal of Agricultural Economics*, *84*(3), 660–678.

Herbel, K., & Langemeier, M. (2012). Persistence in financial performance, 2007-2011. *Kansas Farm Management Association Newsletter,* July/August/September 2012, http://www.agmanager.info/news/KFMA_News/Archives/Jul-Aug-Sep_12.pdf.

Ibendahl, G. (2013). Are the most profitable farms consistently the most profitable? Paper presented at the 19th International Farm Management Congress, Warsaw University of Life Sciences, Warsaw, Poland. July 21–26.

Jung, J. (2006). Estimating Markov transition probabilities between health states in the HRS dataset. https://juejung.github.io/papers/markovtransitions.pdf.

Key, N., Prager, D., and Burns, C. (2017, February). *Farm household income volatility: An analysis using panel data from a national survey.* Economic Research Report No. 226, U.S. Department of Agriculture, Economic Research Service.

Kuethe, T., Paulson, N., & Schnitkey, G. (2015). Crop insurance's role in farm solvency. Paper presented at the Agricultural & Applied Economics Association and Western Agricultural Economics Association Annual Meeting, San Francisco, July 26–28.

Langemeier, M. R., & DeLano, F. D. (1999). Characteristics of highly efficient farms. Paper presented at the Western Agricultural Economics Association Annual Meeting, Fargo, North Dakota, July 11–14.

Li, X., & Paulson, N. D. (2014). Is farm management skill persistent? Selected paper prepared for presentation at the Agricultural & Applied Economics Association's 2014 Annual Meeting, Minneapolis, July 27–29.

Mishra, A., Wilson, C., & Williams, R. (2009). Factors affecting financial performance of new and beginning farmers. *Agricultural Finance Review*, *69*(2), 160–179.

Muller, M. R., & Middleton, J. (1994). A Markov model of land-use change dynamics in the Niagara Region, Ontario, Canada. *Landscape Ecology, 9*(2), 151–157.

Nivens, H. D., Kastens, T. L., & Dhuyvetter, K. C. (2002). Payoffs to farm management: How important is crop marketing? *Journal of Agricultural and Applied Economics, 24*(1), 193–204.

Park, T., Ahearn, M., Covey, T., Erickson, K., Harris, J., Kuethe, T., McGath, C., Morehart, M., Morton, A., Vogel, S., Weber, J., Williams, R., & Wozniak, S. (2010). Agriculture income and finance outlook. United States Department of Agriculture, AIS-90.

Skaggs, R., & Ghosh, S. (1999). Assessing changes in soil erosion rates: A Markov chain analysis. *Journal of Agricultural and Applied Economics*, *31*(3), 611–622.

Sonka, S., Hornbaker, R., & Hudson, M. (1989). Managerial performance and income variability for a sample of Illinois grain producers. *North Central Journal of Agricultural Economics, 11*(1), 39–47.

Urcola, H., Schnitkey, G., Irwin, S., and Sherrick, B. (2004). Testing for yield persistency: Is it skill or is it luck? Paper presented at the American Agricultural Economics Association Meetings, Denver, Colorado, August.

Yeager, E. A., & Langemeier, M. R. (2011). Productivity divergence across Kansas farms. *Agricultural and Resource Economics Review, 40*(2), 282–292.

Zech, L., & Pederson, G. (2003). Predictors of farm performance and repayment ability as factors for use in risk-rating models. *Agricultural Finance Review*, *63*(1), 41–54.