# Is Farm Management Skill Persistent?

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**ABSTRACT**

Farm management skills can affect farm managers' performance. In this article, farm management performance is analyzed based on yearly Illinois Farm Business Farm Management (FBFM) panel data across 6,760 farms from 1996 through 2011. Two out-of-sample measures of skill are used to analyze the ability of farm managers that consistently perform well over yearly and longer time horizons. Persistence tests show management skills are consistent and predictable. Results also suggest that the most skilled managers often generate better financial results.

**Key words:** skill, persistence, farm management, performance.

**JEL Codes:** Q12, Q13, M11

# Is Farm Management Skill Persistent?

The purpose of this study is to conduct tests to evaluate the existence of farm management skills that reveal themselves through persistent financial performance. We use individual farm level data from Illinois FBFM over 1996 to 2011. Unlike the previous literature, we study the observed actions and decisions of farms operators rather than estimating optimal actions or decisions. For instance, the previous literature has focused on optimal strategies and decisions without investigating farm management differences (Plumley and Hornbaker, 1991; Ford *et al.*, 1994; Misha *et al.*, 1999; Malcolm, 2004; Kemp *et al.*, 2004).

Although a useful starting point, previous studies have important limitations. One notable limitation is that none focus on long-term performance in relation to the persistence of farm management skill. In the most complete evaluations to date, a maximum of eight time-series observations were available (Sonka *et al.*, 1989). In this study, we distinguish our work from previous research with the time dimension, by assessing whether farm managers display persistent profit-making ability over a longer period of time, up to 16 years, controlling for farm characteristics. More importantly, little formal research has addressed this issue in terms of skill persistence. Given the multitude of farms, many could have consistently large returns by chance. A common approach to this problem is to test for persistence. The testing approach applies well known methods used in financial literature (Elton *et al.*, 1987; Malkiel, 1995; Carhart, 1997; Aulerich, *et al*. 2013) to see if some managers consistently outperform other managers. Following these studies, we include performance persistence tests. The actions of managers who have consistent performance can be used to identify styles with superior performance. The main finding of this study is that there are better farm managers and their management skills persist.

## Literature Review

Issues facing agricultural producers include commodity and input price volatility, as well as supply-and-demand dynamics driven by exogenous forces such as weather, disease, and macroeconomic conditions. Furthermore, production agriculture has certainly not been immune to crises. The recent credit crisis has had a direct impact on the growth of farm income and farmland values (Paulson and Sherrick, 2009; Ellinger and Tirupattur, 2009). New farmers are in short supply, and this problem constitutes a threat to U.S. agriculture and the food supply (Gale, 2003; Hoppe *et al.*, 2007). These issues underscore the need for a long-run perspective on farm management skills, as managers whose financial performance was superior in one economic environment could experience difficulties in another.

The two most relevant empirical studies addressing farm management skills are Sonka *et al*. (1989) and Urcola *et al*. (2004), each of which uses data from the Illinois Farm Business Farm Management (FBFM) records. Sonka *et al*. (1989) examine the significant managerial performance differences across 179 Illinois cash grain producers over the period 1976-1983, and the variability of performance is assessed. They use management return as a measure of managerial ability and concluded that price of the output and yield are important factors that affect managerial performance. Urcola *et al*. (2004) use corn yield data from McLean County, Illinois to test whether farming skills influence yields with a focus on short-term performance. Their results support the hypothesis that farmer skill influences yields.

My research extends beyond the 7-year horizon used by Urcola *et al*. (2004). Instead, we test for persistence using a 16-year horizon. Prior studies highlight the need for further research on farm management skills because differences in management style are a common explanation for different net farm income or returns.

The focus of farm management skills is on integrating the technical, economic and human components of a farm business into whole-farm analysis and applying a whole-farm approach to making decisions about profitable use of farm resources. Previous studies on farm performance provide thorough evaluations. Malcolm (2004) suggests that farm managers should use a whole-farm business in their planning and decision-making. Similarly, Kemp *et al*. (2004) find there is a great need for continuous development of higher-level management skills among farmers. For instance, plant science (agronomy) as well as business skills (marketing, operations, finance) must be integrated for optimal management decisions. Other agricultural economists use proxies in management studies. As Kay *et al.* (2012) point out, management skill can be measured by the return to management. According to Kay *et al.* (2012), management return is the residual surplus after a charge for unpaid labor and the interest or land charge on capital are deducted from net farm income. It represents the residual return to the owner for the management input, and it can be variable from year to year. This factor is of interest throughout this paper.

Prior research has documented limited evidence of farm management skills, instead using financial success or differences in expected yields as an indication of skill. However, there is no clear consensus arising from previous studies on what variables accurately represent management skill. Plumley and Hornbaker (1991) extend their analysis to show how grain farmers who maintained lower debt levels, higher liquidity, and a balanced asset mix are consistently better off financially. Ford *et al*. (1994) use latent factors related to dairy, crop, and financial management with herd size to explain farm financial success. Mishra *et al*. (1999) apply logit regression analysis and show that variable costs, ownership, management ability, technology adoption, and diversification are important factors that influence success, including net farm income per dollar of asset, returns to labor and management, and management income. Management ability is used in their regression model as a set of management practices: (1) use of rented/leased land in production process and (2) keeping books and records on farm income and expenditures. In addition, differences in expected yield largely reflect differences in farmers' management ability and return potential (Sherrick *et al.*, 2003). However, these measures should also reflect differences in land productivity, which is relatively exogenous to the farmer's location.

While it is easily accepted that better farm management styles with higher revenue are distinct from those with poor performance, little effort has been made in the empirical literature to incorporate managerial skill persistence into analysis of farm performance. If managerial skill persistence does matter empirically, then the data can be relied upon to indicate the presence of skill effects: heterogeneity and dependence. For example, Goodwin *et al*. (2002) suggest yields improve with experience, which can vary across farmers. The importance of experience implies that experienced farmers could get higher yields than inexperienced farmers even in tough economic years.

Management skill persistence is well documented in the finance literature with mixed results. For instance, Carhart (1997) finds persistence in mutual fund performance does not reflect superior stock-picking skill. Rather, common factors in stock returns and persistent differences in mutual fund expenses and transaction costs explain almost all of the predictability in mutual fund return. Grinblatt *et al*. (1995) find that momentum strategies generate better performance persistence. This is in contrast to Carhart (1997), who finds that transaction costs consume the gains from following a momentum strategy in stocks. These results are sensitive to model specification. Extensive literature also exists on investment performance in the mutual fund and hedge fund industries (see Grinblatt and Titman, 1992; Carhart *et al*., 2002; Kosowki *et al.*, 2006). This literature focuses on the performance of an entire portfolio relative to market benchmarks. Although the results are not easily compared to this analysis, similar methods in measuring skill persistence can be used in the analysis of farm managers.

Following the literature on mutual fund and stock market analysis, two basic questions are addressed in this study:

1. Are there better managers with better skill?

2. If so, do their management skills exhibit persistence from year to year?

There are three purposes for investigating longer-run farm performance across a large pool of data: first, to find evidence of persistent managerial skill explained by readily observable data and proxies for managerial attributes; second, to ascertain if significant differences in performance can be documented for a large group of relatively homogeneous farms by considering performance over time; third, to adopt predictive measurements that actually correlate with the objectives that farm managers are trying to achieve.

This study expands the existing literature in farm management by controlling for survivor bias, and by documenting common-factor explanations for farm performance persistence. Section I presents models of performance measurement and their resulting "alpha" estimates on the appropriate benchmark. Section II discusses the data set corrected for survivor bias. Section III documents and explains the one-year persistence in management skill and further interprets the results of a top-and-bottom performance analysis. Section IV examines and explains longer-term persistence, and Section V concludes.

## Conceptual Framework

In Lucas (1978), there is a production technology and a managerial technology separately. For the former, let $F(l, L, k)$ be the output produced with labor $(l)$, land $(L)$ and capital $(k)$ under "representative" management. Consider a population consisting of farm managers endowed with talent, $\alpha$, a skill characteristic, drawn from a fixed distribution $\Gamma: R^{+} \rightarrow [0,1]$. We model managerial technology by a function $MT = \alpha G[F(l, L, k)|\alpha]$ which measures the productivity at a given skill level. A continuous distribution of skills $\alpha$ is analogously represented by

$$S(\alpha) = \int \alpha G(\alpha) d\Gamma(\alpha), \quad (1)$$

where $G(.)$ is monotonically increasing and concave.

Assume markets are competitive and agents act as price takers (normalize the output price to 1). Then the income to manager will be the residual:

$$MR = \alpha G[F(l, L, k)|\alpha] - wl - uL - vk. \quad (2)$$

There is a measure of farm-specific total factor productivity (TFP), which includes farm management skill $(\alpha_i)$, soil productivity $(Spr_i)$, and a random shock $(\varepsilon_i)$ where $\varepsilon_i$ is *i.i.d*. Let $A$ denote the measure of TFP, where $A_i = (\alpha_i,\ Spr_i,\ \varepsilon_i)$. Farms produce output y using inputs $(l, L, k)$ and TFP. Thus, production function (in Cobb–Douglas form) is given by:

$$F(l, L, k) = Al^a L^b k^c. \tag{3}$$

Consider a farm manager $i$. Let the parameter $\alpha_i$ reflect the manager's unobservable management skill. Let $y_i\ (x_i)$ denote a production function of a vector $(x_i)$, where $x_i = (l_i, L_i, k_i)$ and $c_i(x_i)$ denote a cost function. In a profit maximization problem, the expected payoff to manager *i* in equation (2) is:

$$MR_i = Max_{x_i}\ E\ [\pi_i\ (py_i\ (x_i) - \ c_i\ (x_i)\ |z_i, \alpha_i)]\ , \tag{4}$$

where $\pi(.)$ is a profit function; $c_i$ is total cost of inputs; $p$ is a stochastic output price; $y_i$ is stochastic yield; $x_\mathrm{i}$ represents a vector of management decisions (*i.e.* input choices); $z_i$ represents farm characteristics (*i.e.* soil productivity and farm size) and $\alpha_i$ is managerial skill. Thus, $\alpha_i$ can be measured directly. It is a residual, which accounts for effects in management return not caused by farm characteristics.

In this study, farm management skill relates to the ability to combine all of the farmer's resources in an efficient manner. It is conceptually assumed that $\pi_\alpha > 0$, or that greater management skill will increase profitability. In other words, a manager with higher skill will have more management return given the same resources.

I apply the same procedure to management returns using several models of performance proposed by past literature. These include the simple one-factor model of Jensen (1968), the three-factor model of Fama and French (1993), the four-factor model of Carhart (1997), and several models that include conditional factors from the papers of Grinblatt and Titman (1992), Carhart *et al*. (2002), and Kosowki *et al.*

(2006). In the context of the present study, implementation of the multi-factor model approach involves two steps. The first step is to compute the average benchmark and then subtract the benchmark from each farm performance proxy. The second step is to apply the multi-factor models to compute ordinary least square (OLS) estimated alphas (multivariate generalization of Jensen's alpha) using the time series of yearly management returns for each farm *i*.

## Procedures

A major problem with using the profit function in equation (4) is specifying a variable that can proxy for managerial skill (Urcola *et al*., 2004). Farm management skills can be investigated through profitability, which can be measured by the return to management (Kay *et al.*, 2012), defined as the portion of adjusted net farm income that remains after the total costs have been subtracted. It represents the residual return to the owner for management input. Thus, we define management return as follows:

$$Ret_{it}(\$/acre) = \frac{P \times Y_{it} - C_{it}}{Acrtil_i} = \frac{Rev_{it} - C_{it}}{Acrtil_i}, \quad (5)$$

where $Ret_{it}$ is management return per acre ($/acre) on farm *i* for time period *t*, $P$ is the output price, $Y_{it}$ is the total yield; $Rev_{it}$ is the total revenue (the sum of all operator's share of gross sales plus net change in inventory and capital accounts); $C_{it}$ is the total cost (all expenses for items purchased, including interest paid, unpaid labor and the value of family labor, and annual depreciation); $Acrtil_i$ is the farm size measured by tillable acre.

Management on the farm can be measured by the ability of the farmer to optimize the use of natural endowments and inputs to obtain an output. Therefore, the management dimension can be embodied by input expenditures. Farm managers have direct control of these expenses and finding which critical input to manage more effectively is of interest to understanding the persistence of performance. Consequently, input variables are used as determinant variables of persistence. The use of management return as a sole accounting performance measure, however, is a dollar amount and does not accurately reflect use of inputs. Also, the form of farm business (family owned/enterprise) can cause problems for interpretation of this result. To take the heterogeneity of the costs of different farms into consideration, we use a ratio to measure the percentage return with respect to the total cost per acre. This ratio of performance measure is used to evaluate the efficiency of managerial skill or to compare the efficiency of a number of different managers:

$$Ratio_{it}(\%) = \frac{(Rev_{it} - C_{it})/Acrtil_i}{C_{it}/Acrtil_i} \times 100 \;=\; \frac{Ret_{it}\ (per\ acre)}{C_{it}\ (per\ acre)} \times 100\,. \qquad (6)$$

The modified economic performance measure is defined in equation (6). We employ the passive benchmark produced by the average ratio at a county level (Irwin *et al*., 2006) so that the model can focus on managerial skill as a percentage. The regression model derived from equation (4) only contains management return $(\pi_i)$, cost ( $c_i$), farm characteristic factors $(z_i)$, and management skill $(\alpha_i)$ explicitly as follows:

$$Ratio_{it} = \alpha_i + \beta Z_{it} + \gamma Ratio_{jt} + e_{it} \,, \tag{7}$$

$$if\ \gamma = 1, \qquad then$$

$$Ratio_{it} - Ratio_{jt} = \alpha_i + \beta Z_{it} + e_{it} \,, \tag{8}$$

where

$Ratio_{it}$ = the ratio of return to cost of farm *i* for time period *t*;

$Ratio_{jt}$ = the ratio of average return to average cost of county *j* for time period *t*, which is normalized ( assume $\gamma = 1$, held constant across time); [2]

$\alpha_i$ = the constant term;

$Z_{it}$ = a vector of the farm characteristics, which contains soil productivity ($Spr_{it}$) and farm size ($Acrtil_{it}$); [3]

$e_{it}$ = the regression residual;

*i*, *j*, *t* = subscript indexes for farm, county, and year, respectively.

We use the modified economic performance measure as a proxy for skill, which is an accounting identity that includes cost ($c_i$) and yield ($y_i$) as its

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[2] County *j* refers to the county which contains farm *i*, so that $Ratio_{jt}$ can be treated as a benchmark for farm *i*.

[3] The effects of location, weather, and precipitation on profitability are not taken into consideration similar to most research, because this analysis would control for these effects. The variability in temperature, and to a lesser extent in precipitation, are similar within a county. Also, these variables are not exactly linearly related to profitability so it is hard to predict the management skill in terms of functional form. Thus, we follow the method used by Sonka (1989) and control farm characteristics.

determinants in equation (4). Hence, including return as an independent variable does not include cost and yield as regressors in the same regression model in equation (8). Another potential variable, price ($p$), is assumed as given by the price-taking assumptions and hence price is not included in the regression model.

In this model, the county-level average measure was selected to minimize the impact of geography and weather on returns. $(Ratio_{it} - Ratio_{jt})$ is the excess ratio; $\alpha_i$ is the ratio left unexplained by the benchmark model. Accounting for the variation in returns associated with $Z_{it}$ (which contains $Spr_{it}$ and $Acrtil_{it}$) then allows me to better focus on the effects of farm management, indicated by $\alpha_i$ or the intercept. An alpha greater than zero means a farm manager outperforms the expected performance (see Jensen,1968; Fama and French, 1993; Carhart, 1997; Kosowki *et al.*, 2006).

Managerial capacities can then measure cost management or profit-making capacities at the farm level. However, natural endowments, such as soil quality and favorable weather conditions, may disguise the manager's actual capacities. Therefore, quantifying how much management and natural endowment matter respectively in persistence is of interest. In addition, some dimensions that are not directly related to the production process may be captured by a secondary effect, such as the size of the farm. The above discussion motivates our choice of the variables in the farm characteristic vector $Z_{it}$ .

Profitability is impacted by a number of factors, many of which are controlled to some extent by the management decisions of the farm operator. However, the effect of farm size on profitability is an issue continually analyzed and debated by agricultural economists (see Purdy *et al.*, 1997; Garcia *et al.*, 1982; Goodwin *et al.*, 2002). We suggest there may be increasing returns to scale for grain farms, or a normalized measure of profitability (i.e. net farm income per acre) may be enhanced by expanding the scale of the operation. Therefore, in order to gain some insights, We employ two variants of multi-factor market regression model to measure performance.

$$Model\ I: Ratio_{it} - Ratio_{jt} = \alpha_i + \beta_1 Spr_{it} + e_{it}\ . \tag{9}$$

The second representative model is a two-factor model that controls for farm size. Hence, it extends equation (9) as follows:

$$Model\ II: Ratio_{it} - Ratio_{jt} = \alpha_i + \beta_1 Spr_{it} + \beta_2 Acrtil_{it} + e_{it}\ . \tag{10}$$

To identify the superior farm managers, we use the above representative models to compute OLS-estimated alphas using the time series of yearly management returns for each farm *i*.

## The "Hot Hand" Phenomenon: Persistence Test

In this section, we assess whether farm managers display one-year persistent profit-making skill. Two out-of-sample tests of persistence are used in the analysis, both of which have been widely applied in studies of market performance (see Elton *et al*., 1987; Malkiel, 1995; Carhart, 1997; Irwin *et al*., 2006).

In the previous section, we defined a simple model to measure each farm manager's performance to examine if farm management skill exists. Given the number of managers in the market, the laws of probability would suggest that a certain number can outperform the average over long periods, not because of their skills but because they are lucky. It would not, however, be consistent if a disproportionately large number of these managers have the same skill. Thus, to earn a place on the "honor roll" (Malkiel, 1995), a farm not only has to have an extraordinary long-run performance record based on total returns, in this study based on a 16-year period (succinctly illustrated in the previous section), but also has to be a consistent performer. Several financial studies, such as Grinblatt and Titman (1992) and Malkiel (1995), present strong evidence in favor of a "hot hand" phenomenon, which is when mutual funds that achieved above-average returns continue to enjoy superior performance.

In *each year*, we estimate a *cross-section* regression:

$$Ratio_i - Ratio_j = \beta_1 Spr_i + \beta_2 AcrTill_i + \mu_i \,, \tag{11}$$

where $\mu_i$ is the residual of equation (11), and

$$\alpha_i \equiv Excess\ Ratio_i - E[Excess\ Ratio_i] = \mu_i \,, \tag{12}$$

where

$$Excess\ Ratio_i = Ratio_i - Ratio_j$$

$$E[Excess\ Ratio_i] = \beta_1 Spr_i + \beta_2 AcrTill_i$$

In this specification, alpha is represented by the residual of equation (11), which is the excess ratio left unexplained by the benchmark model in equation (12). An alpha greater than zero means a farm manager outperforms the benchmark.

If some farmers have persistent performance, then it can be explained that they have consistently better skills than others. Farmers receiving above-average returns might be using a superior management skill, so finding performance persistence could help identify superior strategies. We test for persistence two ways, using the Spearman ranking test and the winner and loser ranking test.

**Spearman Ranking Test**

The first test is the Spearman ranking test, which is a paired correlation analysis across adjoining periods.[4] Persistence simply means that the actual statistic is correlated from one period to the next throughout the sample periods. For instance, if financial performance of farm *i* statistically outperformed the benchmark in 2011, it would be correlated highly with the good performance in 2012. Therefore, for a single farm manager, whether alpha rankings in consecutive periods are positively correlated would be a measure of persistence which means the statistic is indicative of skill. We

[4] Spearman's (1904) rank correlation is calculated as Pearson's correlation coefficient computed on the ranks and average ranks (Conover 1999, 314-315). The significance is calculated using the approximation: $p = 2 \times$ ttail$(\mathrm{n} - 2, |\hat{\rho}|\sqrt{n-2} \,/\, \sqrt{1-\hat{\rho}^2})$.

also perform the Spearman nonparametric test on the rank ordering of performance measure because it has some statistical advantages, *i.e.* it does not assume a linear relationship between variables. Correlations are calculated using pairwise deletion of observations with missing values due to an unbalanced data set. We use casewise deletion, where observations are ignored if any of the variables are missing. Here, the null hypothesis is that the performance measure is randomly ordered.

**Winner and Loser Ranking Test**

Mirroring the previous discussion, the second test is a winner and loser ranking test that assesses, in a nonparametric context, whether managers in the top half of the alphas distribution in a time period continue in the top half of the distribution in the next period. Farms with high past alphas demonstrate relatively higher alphas and expected returns in subsequent periods. The null hypothesis is the past ranking of a farm manager does not help predict the manager's future ranking.

This test is based on placing farm managers into winner and loser categories across adjacent pairs of years. The first step in this test procedure is to form the sample of all farm managers that are present in the pair of years. The second step is to rank each farm manager in the first year of the pair (*e.g.*, $t$ =1996) based on alpha estimates from equation (12). Then, the managers are sorted in descending rank order. The third step is to form two groups of mangers in $\text{year}_t$: a winner is defined as a manager's alpha ranking that has achieved above the median; a loser is defined as a manager's alpha ranking that has achieved below the median. The fourth step is to rank each farm manager in the subsequent $\mathrm{year}_{t+1}$ of the pair (*e.g.*, 1997) based on alpha estimates and once again form winner and loser groups of farm managers. The fifth step is to compute the following category counts for the farm managers in the pair of years: $\mathrm{winner}_t - \mathrm{winner}_{t+1}$, $\mathrm{winner}_t - \mathrm{loser}_{t+1}$, $\mathrm{loser}_t - \mathrm{winner}_{t+1}$, $\mathrm{loser}_t - \mathrm{loser}_{t+1}$. The sixth step is to construct a 2×2 contingency table formed on the basis of winner and loser counts. The appropriate statistical test in this case is Fisher's exact test, a nonparametric test that is robust to outliers because both row and column totals are predetermined in the contingency table. The null hypothesis is that the relative proportions of $\mathrm{year}_t$ are independent of $\mathrm{year}_{t+1}$. With large samples, a Pearson's chi-squared test can also be used.

I also calculate the percentage of winners in the initial year that remain in the upper 50% in the subsequent year. If these conditional probabilities are higher than what would result from flipping a coin (randomness), they can provide predictability. The disadvantage of this repeat winners and losers approach is that it has low power to reject the null hypothesis of no performance persistence (Cunningham III *et al.*, 2007). A fuller description of the variables involved follows.

## Data

This research requires a panel of individual and detailed farm-level data. The data set contains continuous observations for a sample of 6,760 farms in the state of Illinois over 16 years, from 1996 to 2011, collected from the Illinois Farm Business Farm

Management (FBFM) survey. The FBFM records include a variety of financial and agronomic characteristics for each cooperating farm operation. The most relevant empirical study addressing individual farm managerial skill is Urcola *et al*. (2004), which also uses data from the FBFM. FBFM data prior to 1996 is summarized in a different manner (Urcola *et al*., 2004). Due to the data change, we focus on the time period from 1996 to 2011 for this analysis. This study extends beyond the 7-year horizon used by Urcola *et al*. (2004). Instead, we test for persistence using a 16-year horizon. Also, the prior research's sample is limited to only one county in Illinois, but does not consider different regions of the state. Finally, other prior studies have focused on in-sample estimates of the correlation in performance measure rather than out-of-sample estimates that are the standard in investment studies (e.g. Malkiel, 1995). An out-of-sample measure is a more stringent test of the persistence of profit in farm management.

In this research, we restrict the analysis to corn and soybean farmers, who are defined as having 95% or more of gross revenue coming from crop revenue and less than 5% of farm receipts coming from livestock sales. Within Illinois, acreage of farms enrolled in FBFM account for approximately 25% of the acres in corn and soybean production. To be selected from a large pool of FBFM cooperator data, each farm record had to have been certified usable by the FBFM field staff representative with 180 or more tillable acres.

For each of the farms, the farm ID combined with county ID results in a unique farm identification marker and is used to isolate management return ($/acre) on each farm. Ninety-eight counties in total are investigated. All FBFM expenses were adjusted for prepaid expenses, accounts payable and cash settlements. The enterprise analysis reports all the costs related to each farm for a given year. Total costs can be further broken down into three categories: 1) direct costs include fertilizer, seed, pesticides, drying, and storage; 2) power costs include machinery repairs, equipment depreciation, machine hire and lease, and fuel; 3) overhead costs include land, hired labor, building repairs and deprecation, insurance, and interest. In the dataset, revenues include crop revenue, livestock revenue, custom revenue and other revenue. Total gross revenue after the total cost is the management return.[5]

FBFM reports a soil productivity ratio (SPR) based on maps of soil types for each Illinois farm, following Fehrenbacher *et al.* (1978). The SPR is an average of yield potential on a farm weighted by the soil types within the farm. The SPR ranges from 40 to 100, with 100 being the most productive soil quality, and was calculated at the farm level based on soil structure and quality as well as suitable crops. It directly embodies the potential productivity of the soil for main crops like soybean and corn. Therefore, the expected effect on returns should be positive as better soil should not need more use of chemicals to compensate for deficiencies.

[5] The costs and returns are matched up to the same crop/calendar year. But we also noticed they may not be matched up to the same production/marketing year. For instance, corn that is harvested in October of one year may not be sold until the following calendar year or longer. This says that returns may have various components which could include the returns to storage. Similarly, inputs for the next production cycle which begins with planting in May may be purchased immediately after the last harvest (between October and December) rather than in the year that it is going to be used. Since the FBFM data account for the accrual management return within calendar year by recording both old crop and new crop, which means marketing/production year returns are adjusted for each year on an accrual basis, for the simplicity of this model, we assume that there are no storage costs for crops.

Total tillable acres for each farm are the indicators of farm size. While Purdy *et al.* (1997) show that larger farms outperformed smaller farms in Kansas, Garcia *et al*. (1982) do not find any significant relationship between size and success. In this research, it is hypothesized that persistent high-return farms produce more acres than other farms.

It is possible that farmers with low skills are naturally eliminated from our database as their farms go out of business. This might create substantial survivorship bias, leaving only highly skilled farmers who are able to maintain high returns through time. Survivorship bias would likely cause an overstatement of returns obtained by farmers, a consequence of tracking only farms that remain in business at the end of sample period. Thus, survivorship bias is an important issue in mutual fund research (See Brown *et al.*, 1992; Malkiel, 1995; Carhart, 1997; Carpenter and Lynch, 1999) since it is typical of mutual fund and hedge funds databases. However, our sample is, to our knowledge, the largest and most complete survivorship-bias-free farm database currently available. Urcola *et al*. (2004) use a similar database obtained from FBFM to study the effect of farmer skills on yields. The sample in their study is stable with an average attrition rate of 6.9% and an average entry rate of 5.8%. In addition, the comparison of mean yields of farmers present in all years and the whole group of farmers imply that survivorship bias effects can be considered negligible.

Table 1 reports descriptive statistics of the farm data. Our sample includes a total of 6,760 diversified farms over 16 years. The data set was cleaned by omitting the outliers. We used a simple rule of thumb, $z = 3$ guideline (i.e. data points three or more standard deviations from the mean of $Ret_i$), as an initial screening tool, and depending on the results of that screening, examined the data more closely and modified the outlier detection strategy accordingly. The sample includes 55,015 total observations with per acre average return of $43.34 and average expenses of $614.22. In addition, the excess ratio in the sample is 1.06%. Also, over the full sample, average farm size is 914.07 acres and the average soil productivity index value is 79.89.

One way to consider the changes to management return by top/average/bottom comparison is to analyze the annual change in management return. To examine the long-term difference in farm returns related to heterogeneity in the characteristics of the farms on the top and bottom. We employ a cross-sectional analysis for top and bottom farms in each year. Management return and ratio (modified economic performance measure) data for each category (top 10% farms/average of all farms/bottom 10% farms) are shown in figure 1 and figure 2. Figure 3 and figure 4 present the spatial distribution of the modified economic performance estimates. In general, the characteristics which stand out are that (1) more successful farm managers tend to live in central and northern Illinois; (2) and the within-county performance ranges across the state may vary.

These results clearly document that substantial long-term differences in farm performance have occurred within this sample of relative heterogeneous farms.

## Results

### Are There Better Managers?

I employ two models of performance measurement. Results for the various models are highlighted in table 2. Data across sample years were estimated for every single farm. The total number of farms present during the sampling period in the FBFM database is 6,760. A subset including only the farms present for more than 10 years was constructed to take into account the enough degrees of freedom. This subset includes a total of 1,631 farm-level observations for each variable for Model I and 1,624 total observations for Model II.

The results are consistent across various types of functional forms. Table 2 presents estimated alphas from two models. In this table, the first row shows the number of farms with usable data based on our data restrictions. The second row through the fifth row display significantly positive/negative alpha numbers and percentages. Results suggest that there are superior farm managers who produce benchmark-adjusted expected returns in the long run. For instance, the first column (Model I) shows that out of 1,631 available observations, 98 (84) farms have significant positive (negative) alphas. The second column (Model II) shows that out of 1,624 available observations, 79 (81) farms have significant positive (negative) alphas. Table 2 also shows that only 4.86% (4.99%) farms have positive (negative) alphas in Model II compared to 6% (5.15%) in Model I. The number of significant alphas drops, when we decouple farm size from the previous (Model I) manager skill set, because what is left unexplained are pure management skills without the impacts from farm characteristic factors (Model II).

When addressing a real farm performance analysis, there are many variables and interactions, and identifying the effects of individuals is a vastly more challenging task worth testing. Some of the natural conditions, such as the soil productivity for particular farms, may be more favorable, which would cause the measure of a manager's capacities not to be as accurate. Therefore, quantifying how much actual management and natural endowment affect management skill persistence is of interest. In addition, results show that Model I has a slightly inflated number of farms with positive alphas as compared to Model II. Thus, in order to avoid measurement bias, the size of the farm has to be taken into account. Based on these findings, we will focus further detailed analysis and testing on the strongest results from the analysis of Model II.

Estimates of the regression in equation (10) are shown in table 3. The pooled results in table 3 indicate a strong relationship between financial performance and both soil productivity and farm size. The expected effect of *Spr* on returns should be positive as better soil contributes to higher yields and should not need more use of chemicals to compensate for deficiencies, minimizing the related costs. The average parameter of *Spr* is 0.0732, which indicates that the higher soil productivity, the higher the expected return earned. The pooled estimated significant coefficient of *Spr* in Illinois is what motivates the separation from management returns. Significantly positive estimates of *Acrtil* (0.007) suggest that there may be increasing returns to scale for grain farms, or a normalized measure of profitability may be enhanced by expanding the scale of the operation.

Recall that the primary interest in this study is to identify the superior alphas and examine the farm management skill persistence of the best farm performance. When evaluating these highly significant results, we find that farms with high alphas demonstrate relatively higher modified management returns in sample periods. It is conceptually assumed that $\pi(\alpha)$ is an increasing function. Results in table 3 support the hypothesis that the most skilled managers often end up on top. For instance, farms with $\alpha$ value of 30.29 end up in the top 5% in terms of management returns; and farms with $\alpha$ value of 19.80 end up in the top 10% of management returns earned. In addition, the top 25% of farms earn estimated alphas that are significantly greater than zero, indicating the large positive alphas, net of costs, are extremely likely to arise due to skill. Thus, the best performing farms appear to outperform the county average even though the majority underperform the county-level benchmark ($\alpha$ value for OLS estimation is -11.21 which is significantly less than zero). Based on these results, good managers can be compared with poor managers. For instance, they could be assigned an alpha ranking where the 5% of managers with the best performance receive an alpha of 30.29, and the 5% of managers with the worst performance receive an alpha of -51.23. The difference between a good manager and a poor manager could reach 81.52, given their alpha values (30.29-(-51.23) = 81.52).[6] These results strongly support farmer managerial skill having an influence on returns and this is sufficient to provide overwhelming evidence that some farm managers have superior skills. These findings are also true when compared to Model I, using the estimation without farm size as the explanatory variable. [7]

**One-year Persistence Test**

The Spearman rank correlations for alphas are shown in table 4. Table 4 shows the $p$-values for the null hypothesis that the past ranking of a farm manager's alpha does not predict the manager's future ranking ($H_0\colon \rho = 0\ versus\ H_a\colon \rho > 0$). Rank correlations are all significant and positive between adjacent years. In this case, random rank-ordering is rejected. Rank correlations for alphas vary between the adjacent years and have an overall average of 0.3935. Thus, results indicate that, even after controlling for soil productivity and farm size, some farmers still have consistently better skill than other farmers. However, since the Spearman test treats the ordering of winner and loser categories equally, it lacks power against the hypothesis of predictability in performance.

Table 5 shows the number of winners and losers conditional on the previous year's performance based on alpha ranking. On average, the percentage of repeated

[6] The 81.52 economic difference (not exact difference) implicitly assumes that the good and bad manager we are comparing live in the same county and thus have the same benchmark. If one looks into figure 3 and figure 4, which show the spatial distribution of the % return estimates, there might be quite different benchmarks and the within-county ranges across the state may vary. It is therefore difficult to compare across counties.

[7] The analysis is available upon request and only excluded here due to page constraints.

winners is 64.75% (the conditional probabilities are higher than 25%, *i.e.* what would result from flipping a coin).

Results show the *p*-values for the Fisher's exact tests of the null hypothesis that the past ranking of a manager's skill does not predict the manager's future ranking. The null hypothesis that a winner and loser are randomly determined is rejected in all years. These results are consistent with the conclusions of the correlation analysis shown in the previous section and support the hypothesis that a farm manager's skill influences financial performance and persists.

The consistency table is displayed in figure 5. The bars represent percentage of each category. From the figure, it is apparent that winners are somewhat more likely to remain winners, and so are losers. The ranks of top farm managers persist, but so do the poor managers.

**Long-term Persistence Test**

The predictability results presented so far are based on one-year comparisons. It is possible for performance to be unpredictable over longer time horizons, but predictable over shorter horizons. To reduce the noise in past performance rankings, we repeat our earlier analysis and assess longer-term predictability. The sample is again limited to all 16 crop-years of the Spearman ranking test. The correlations are the rank correlations between a producer's average alpha in a four-year period and alpha in a subsequent four-year period (Cunningham III *et al.*, 2007). Alpha rankings are averaged for each of the farm managers during the initial four years (*e.g.*, 1996–1999) and the subsequent four years (*e.g.*, 2000–2003). Tests of predictability are then applied to the two sets of long-term averages.

Results are similar for a longer-term period. Table 6 shows skill persistence in the long-term period in terms of positive rank correlation in two consecutive four-year periods. Table 7 shows the percentage of managers whose alpha ranked in the top 50% in two consecutive four-year periods. All the percentages of repeated winners in longer-term tests are higher than in the one-year tests. The Fisher's exact tests and Pearson's chi-squared tests results reject the null hypothesis that alpha ranking is by chance. Therefore, table 6 and table 7 suggest strong skill persistence in the long run.

## Summary and Conclusions

Using individual farm-level data from FBFM from 1996 to 2011, this study investigates whether managerial skill persists in farm performance. The extent to which the skills used by farm managers are either efficient or not was measured by a two-factor model that includes a benchmark. The benchmark emphasis makes the model applicable to many farm types that differ in geographic location, tenure, and other structural characteristics. Given the evidence documented here, persistent profit-making capacity is an indication of skill. More specifically, about 5% of managers have more efficient skills to outperform the county average in the long run, though the majority show no skill. Average skill efficiency differences between top and bottom managers are large in terms of alpha values. In addition, farm managers appear to benefit from natural endowment (*i.e.*, soil productivity and farm size). Based on previous research (*e.g.*, Malkiel, 1995; Urcola *et al.*, 2004; Irwin *et al.*, 2006), two basic out-of-sample persistence tests – a Spearman ranking test and a winner and loser ranking test – are examined to determine whether farm managerial skill consistently performs well.

Overall results provide compelling evidence that the superior alphas of star managers survive and are not an artifact of luck. While it is difficult for farm managers to always profit, persistence emerges from the Illinois crop market in terms of the rank correlations of alpha. The strongest evidence for persistence exists with Spearman's $\rho$ reaching 0.6 for four adjacent years. The findings identify significant persistence in ranking; managers in the top 50% of the profits distribution in $t$ tend to stay in upper half in $t+1$. On average, 64.75% of winners are also winners in $t+1$. In addition, for both short and long horizons, the Fisher's exact test and Pearson's chi-squared test results appeared to be significant. Thus, our findings using an arguably more rigorous measure – out-of-sample persistence in profit-making skill – are consistent with the hypothesis that skill does exist. With regards to the work by Urcola *et al*. (2004), our findings are consistent with the structure and implication of their models. This evidence, while not extensive in magnitude, may provide support for behavioral theories.

I am also aware of the limitations of this study. A complete comparison of the estimation procedures employed in this study would include a top and bottom performance deciles test that takes into account the magnitude of skill differentials between top and bottom groups. The findings can be further applied to indicate whether management skills are on the cost side, the revenue side, or both. The analysis in this study could also be extended to investigate the characteristics of the most skilled farm managers and their management styles in the performance evaluation. However, more performance profiles and observations per farm manager are needed for this type of analysis.

Applications of persistence tests in skill represent an interesting picture for future studies. The next step in this research should examine how this management skill persistence relates to farm growth, since farms' financial successes depend on management returns. It could be the case that historical expertise may convey important information about optimal production practices in the long run. Thus, it would be valuable to focus on "alpha" as a measure to explicitly capture predictable efficient management skill. The approach implemented in this article provides a framework for more general evaluation of farm management for agencies such as farmers, investors, educators, and policymakers. Lenders and investors will be interested in the degree to which skill influences farm profitability. Funding issues for major lenders and the emerging regulatory design arise from commodity and farm-related credit market activity during the recent financial crisis (Paulson and Sherrick, 2009; Ellinger and Tirupattur, 2009). Thus, potential farm management efficiency needs to be recognized in risk management activities. For future research, the effectiveness of education and training for superior farm management practices could be investigated to identify the types of training most effective to improve profitability. Ultimately, studying farm management skill persistence will help with the challenging task of prediction, and better predictions lead to greater farm performance.

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**Table 1. Descriptive Statistics**

**Illinois, 1996-2011**

| Variable | Definition | Mean | Std. Dev. |
|---|---|---|---|
| $C_i$($/acre) | Total Cost per Farm | 614.22 | 4383.73 |
| $Ret_i$($/acre) | Management Return per Farm | 43.34 | 1770.64 |
| $Ratio_i$(%) | $\frac{\mathrm{Ret_{it}}}{\mathrm{C_{it}}} \times 100$ per Farm | 7.58 | 25.03 |
| $Ratio_j$(%) | $\frac{\mathrm{Ret_{it}}}{\mathrm{C_{it}}} \times 100$ per County | 6.53 | 21.39 |
| $Excess\ Ratio_i$(%) | $\mathrm{Ratio_{it}} - \mathrm{Ratio_{jt}}$ | 1.06 | 21.39 |
| $Acrtil_i$(acre) | Farm Size | 914.07 | 701.67 |
| $Spr_i$ | Soil Productivity | 79.89 | 13.01 |

**Table 2. Farms with Significant Alpha Estimates**
**Illinois, 1996-2011**

| | Model I<br>*Z includes only Spr* | Model II<br>*Z includes both Spr and Acrtil* |
|---|---|---|
| Number of farms with usable data | 1631 | 1624 |
| Number of farms with positive alphas | 98 | 79 |
| Percentage of farms with positive alphas (%) | 6.00 | 4.86 |
| Number of farms with negative alphas | 84 | 81 |
| Percentage of farms with negative alphas (%) | 5.15 | 4.99 |

*Note: 1. t-test is applied for each farm across 16-year-period observations.*

*2. Only significant results at the 5% level are reported above, which reject the null hypothesis that alpha equals to zero.*

## Table 3. Alpha Values across OLS and Different Quantile Regressions

## Illinois, 1996-2011

| | OLS | Quantiles of Modified Management Returns | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Average | 0.05<br>Low | 0.10 | 0.25 | 0.50 | 0.75 | 0.90 | 0.95<br>High |
| *Spr* | 0.0732*** | 0.149*** | 0.143*** | 0.110*** | 0.0786*** | 0.0508*** | 0.0245 | 0.0205 |
| | (10.74) | (8.65) | (13.32) | (13.71) | (10.61) | (5.98) | (1.72) | (1.09) |
| *Acrtil* | 0.0070*** | 0.0085*** | 0.0088*** | 0.0082*** | 0.0072*** | 0.0062*** | 0.0049*** | 0.0038*** |
| | (55.56) | (13.45) | (26.79) | (43.63) | (52.46) | (44.91) | (22.05) | (13.10) |
| $\alpha$ | -11.21*** | -51.23*** | -42.54*** | -27.49*** | -12.07*** | 3.517*** | 19.80*** | 30.29*** |
| | (-19.8) | (-33.7) | (-45.9) | (-40.6) | (-19.6) | (5.02) | (16.97) | (19.69) |
| $R^2$ | 0.055 | 0.050 | 0.055 | 0.047 | 0.031 | 0.018 | 0.010 | 0.006 |

*Note:* *t* statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

**Table 4. Spearman Rank Correlations**

**Illinois, 1996-2011**

| Year | N | Spearman's $\rho$ | $p$-Value |
|---|---|---|---|
| (96-97) | 2710 | 0.418$^{***}$ | 0.000 |
| (97-98) | 2528 | 0.351$^{***}$ | 0.000 |
| (98-99) | 2593 | 0.375$^{***}$ | 0.000 |
| (99-00) | 2692 | 0.405$^{***}$ | 0.000 |
| (00-01) | 2692 | 0.438$^{***}$ | 0.000 |
| (01-02) | 2818 | 0.242$^{***}$ | 0.000 |
| (02-03) | 2764 | 0.415$^{***}$ | 0.000 |
| (03-04) | 2793 | 0.376$^{***}$ | 0.000 |
| (04-05) | 2694 | 0.392$^{***}$ | 0.000 |
| (05-06) | 2605 | 0.446$^{***}$ | 0.000 |
| (06-07) | 2574 | 0.366$^{***}$ | 0.000 |
| (07-08) | 2589 | 0.482$^{***}$ | 0.000 |
| (08-09) | 2547 | 0.359$^{***}$ | 0.000 |
| (09-10) | 2427 | 0.389$^{***}$ | 0.000 |
| (10-11) | 2444 | 0.449$^{***}$ | 0.000 |
| Average | 2627 | 0.3935 | - |

*Note: Null hypothesis is* $\alpha_t$ *and* $\alpha_{t+1}$ *are independent.* $^{***}$ $p < 0.001$

**Table 5. Contingency Tables**

**Illinois, 1996-2011**

| Year *t* | | Year *t*+1 *Winner* | *Loser* | Percentage of Repeated Winners | *p*-Value for Fisher's Exact Test | *p*-Value for Pearson's Chi-squared Test |
|---|---|---|---|---|---|---|
| 1996 | *Winner* | 877 | 480 | | | |
| | *Loser* | 478 | 875 | 0.646 | 0.000 | 0.000 |
| 1997 | *Winner* | 789 | 475 | | | |
| | *Loser* | 475 | 789 | 0.624 | 0.000 | 0.000 |
| 1998 | *Winner* | 814 | 483 | | | |
| | *Loser* | 482 | 814 | 0.628 | 0.000 | 0.000 |
| 1999 | *Winner* | 870 | 476 | | | |
| | *Loser* | 476 | 870 | 0.646 | 0.000 | 0.000 |
| 2000 | *Winner* | 901 | 445 | | | |
| | *Loser* | 445 | 901 | 0.669 | 0.000 | 0.000 |
| 2001 | *Winner* | 819 | 590 | | | |
| | *Loser* | 590 | 819 | 0.581 | 0.000 | 0.000 |
| 2002 | *Winner* | 889 | 493 | | | |
| | *Loser* | 493 | 889 | 0.643 | 0.000 | 0.000 |
| 2003 | *Winner* | 872 | 525 | | | |
| | *Loser* | 524 | 872 | 0.624 | 0.000 | 0.000 |
| 2004 | *Winner* | 868 | 479 | | | |
| | *Loser* | 479 | 868 | 0.644 | 0.000 | 0.000 |
| 2005 | *Winner* | 868 | 435 | | | |
| | *Loser* | 434 | 868 | 0.666 | 0.000 | 0.000 |
| 2006 | *Winner* | 837 | 450 | | | |
| | *Loser* | 450 | 837 | 0.650 | 0.000 | 0.000 |
| 2007 | *Winner* | 887 | 408 | | | |
| | *Loser* | 407 | 887 | 0.685 | 0.000 | 0.000 |
| 2008 | *Winner* | 887 | 408 | | | |
| | *Loser* | 408 | 887 | 0.685 | 0.000 | 0.000 |
| 2009 | *Winner* | 780 | 434 | | | |
| | *Loser* | 433 | 780 | 0.643 | 0.000 | 0.000 |
| 2010 | *Winner* | 827 | 395 | | | |
| | *Loser* | 395 | 827 | 0.677 | 0.000 | 0.000 |
| | | | Average | 0.648 | - | - |

*Note: 1. Null hypothesis is the relative proportions of year(t) are independent of year(t+1).*

*2. Fisher's exact test is a statistical significance test used in the analysis of contingency tables. With large samples, a Pearson's chi-squared test can be used.*

**Table 6. Spearman Rank Correlations**

**Illinois, 1996-2011**

| Year($t$) | Year($t+1$) | Observation | Spearman's $\rho$ | $p$-Value |
|---|---|---|---|---|
| 1996-1999 | 2000-2003 | 974 | 0.605*** | 0.000 |
| 2004-2007 | 2008-2011 | 1222 | 0.519*** | 0.000 |

*Note: Null hypothesis is* $\alpha_t$ *and* $\alpha_{t+1}$ *are independent.* $^{***}$ $p < 0.001$

**Table 7. Contingency Tables**
**Illinois, 1996-2011**

| Year($t$) | | Year ($t$+1) *Winner* | *Loser* | Percentage of Repeated Winners | $p$-Value for Fisher's Exact Test | $p$-Value for Pearson's Chi-squared Test |
|---|---|---|---|---|---|---|
| | | (00-03) | | | | |
| (96-99) | *Winner* | 351 | 136 | | | |
| | *Loser* | 136 | 351 | 0.721 | 0.000 | 0.000 |
| | | (08-11) | | | | |
| (04-07) | *Winner* | 421 | 190 | | | |
| | *Loser* | 190 | 421 | 0.689 | 0.000 | 0.000 |

*Note: 1. Null hypothesis is the relative proportions of year(t) are independent of year(t+1).*

*2. Fisher's exact test is a statistical significance test used in the analysis of contingency tables. With large samples, a Pearson's chi-squared test can be used.*

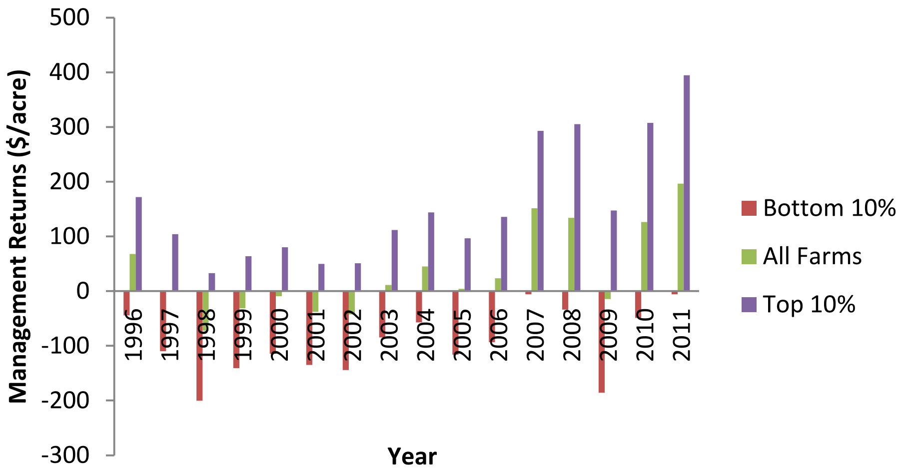


**Figure 1. Management Returns ($/acre) per Year**

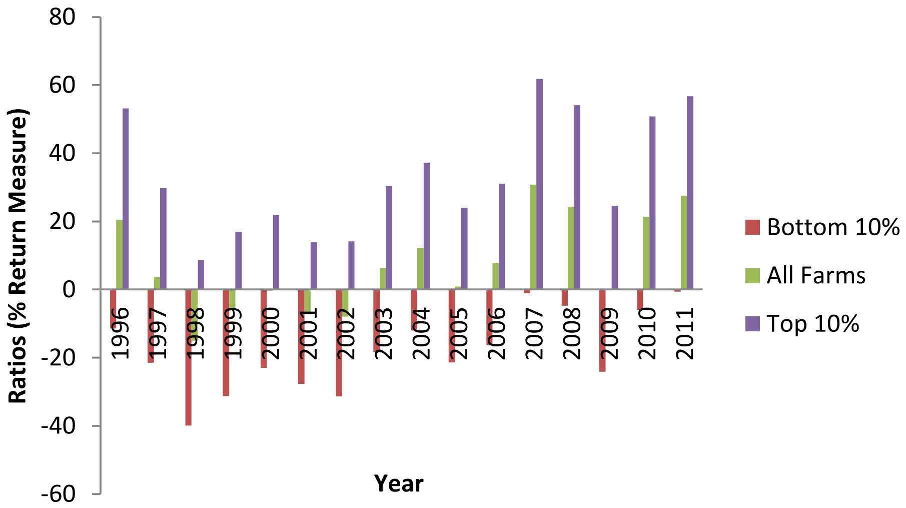


**Figure 2. Ratios (% Return Measure) per Year**

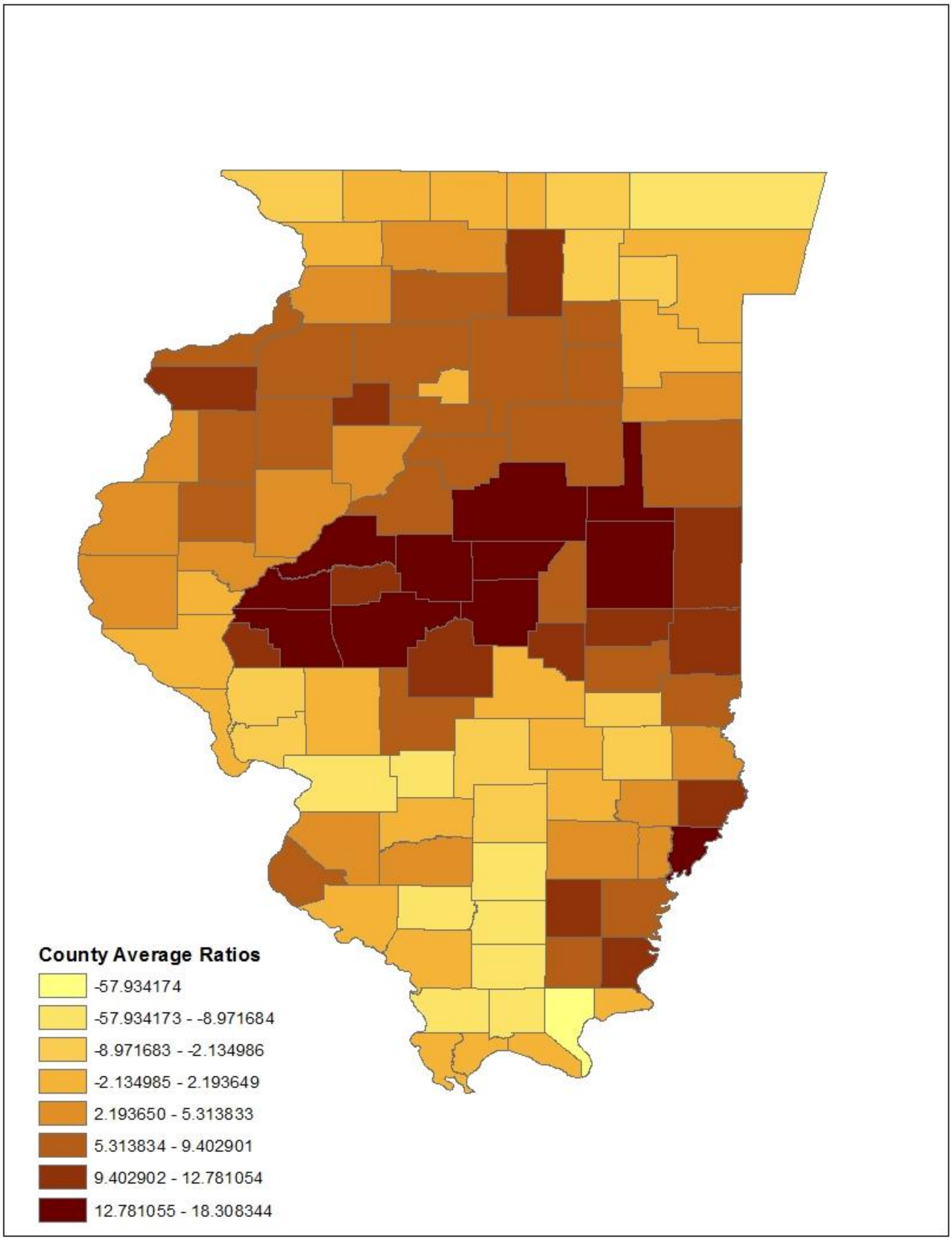


**Figure 3. County Average Ratios**

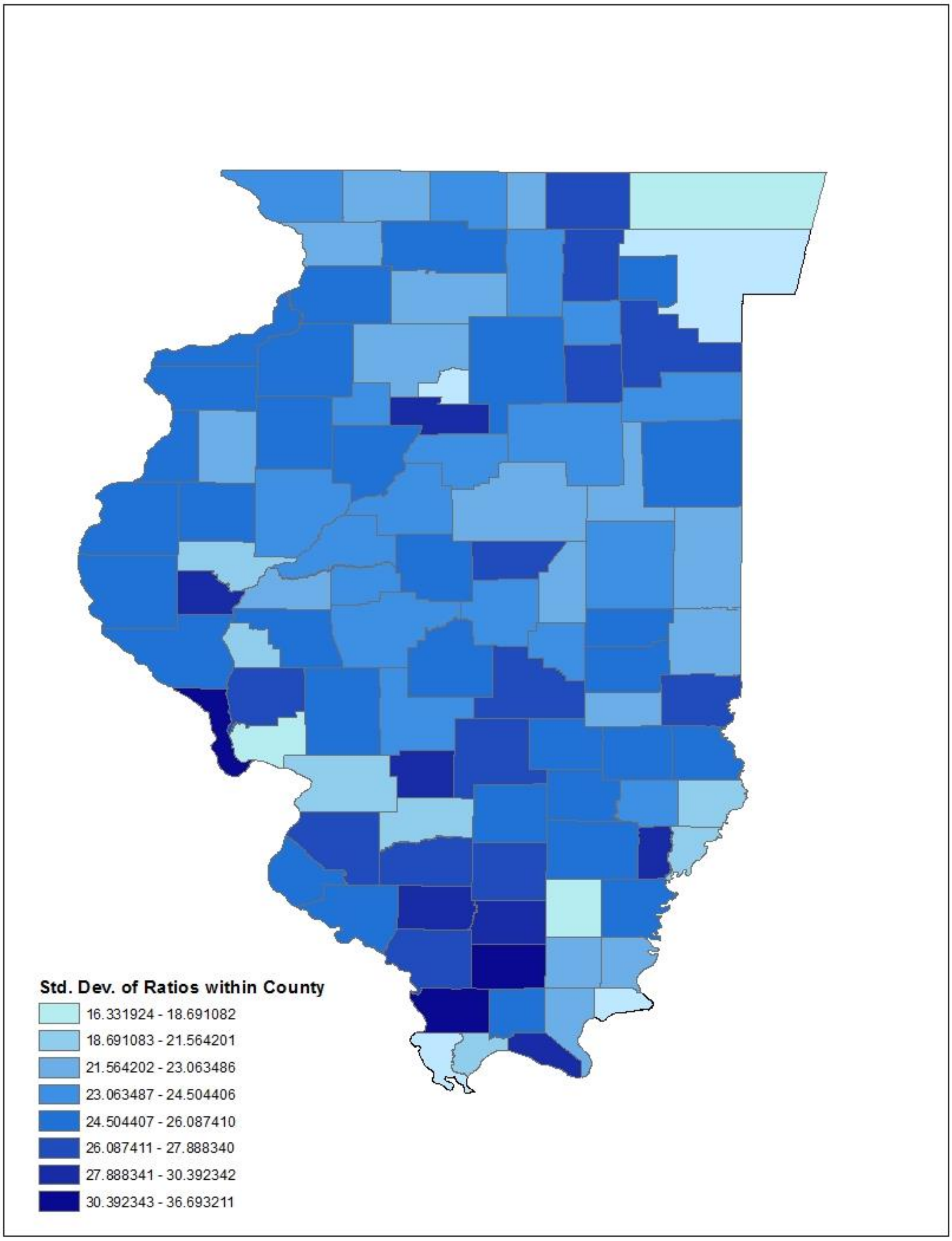


**Figure 4. Standard Deviations of Ratios within County**

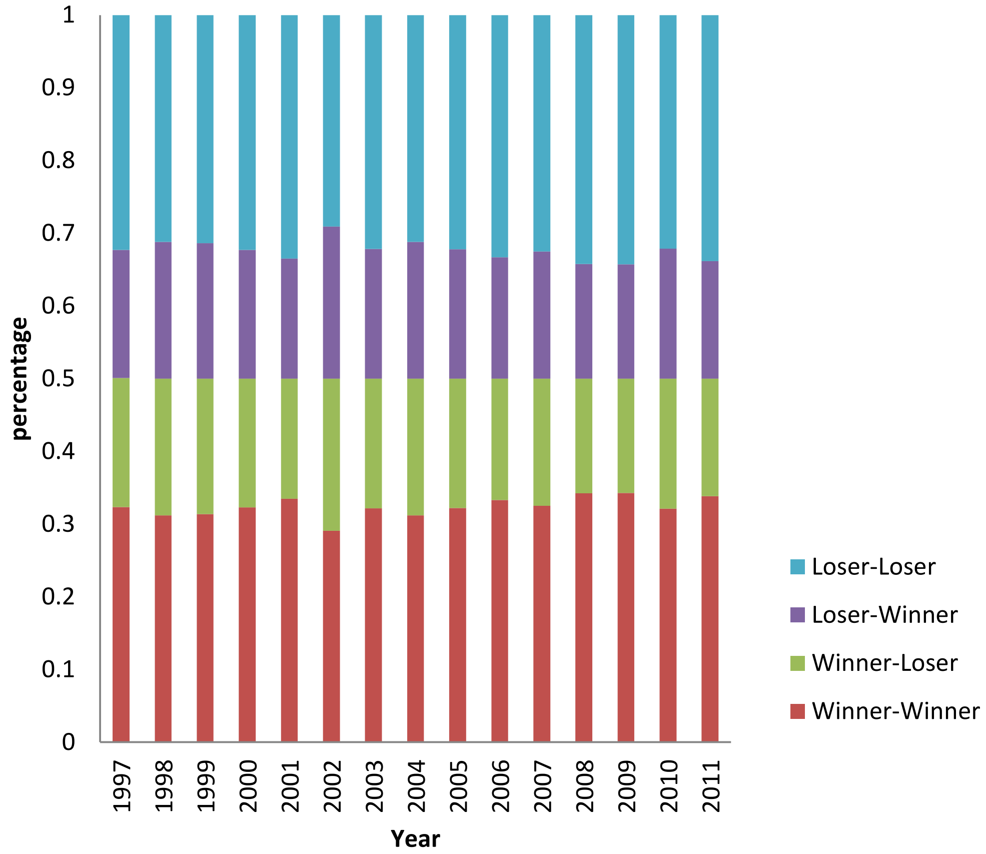


**Figure 5. Percentages of Four Categories per Year**