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Agricultural Finance Review

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Agricultural Finance Review

Department of Applied Economics and Management, Cornell University
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Preface

Agricultural Finance Review (*AFR*) provides a forum for discussion of research, extension, and teaching issues in agricultural finance. This publication contains articles contributed by scholars in the field and refereed by peers.

Volume 43 was the first to be published at Cornell University. The previous 42 volumes were published by the United States Department of Agriculture. *AFR* was begun in 1938 by Norman J. Wall and Fred L. Garlock, whose professional careers helped shape early agricultural finance research. Professional interest in agricultural finance has continued to grow over the years, involving more people and a greater diversity in research topics, methods of analysis, and degree of sophistication. We are pleased to be a part of that continuing development. We invite your suggestions for improvement.

AFR was originally an annual publication. Starting with volume 61, Spring and Fall issues are published. The *AFR* web page can be accessed at http://afr.aem.cornell.edu/. Abstracts of current issues and pdf files of back issues since 1995 are available.

The effectiveness of this publication depends on its support by agricultural finance professionals. We especially express thanks to those reviewers listed below. Grateful appreciation is also expressed to the W. I. Myers endowment for partial financial support. Thanks are also due to Faye Butts for receiving, acknowledging, and monitoring manuscripts, and Judith Harrison for technical editing.

Manuscripts will be accepted at any time.

Calum G. Turvey
Editor

Bruce J. Sherrick
Associate Editor

Biography: John Kenneth Galbraith: The Agricultural Finance Years

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Calum G. Turvey

The death of John Kenneth Galbraith on April 28, 2006, at the age of 97 ended a lifelong dedication to public service and liberal economic thought. A worldly man of intellect and wit, Galbraith was very well known among economists of all stripes who either agreed with him or did battle with him, but his career as an agricultural economist came rather swiftly to an end after the publication of Keynes' (1936) *General Theory of Employment, Interest, and Money*. Although he dabbled in agricultural economics up to at least 1956, he preferred to ride the academic ranks as an economist.

What is not widely known to agricultural economists, and more so to the readership of the *Agricultural Finance Review*, is that Galbraith was trained primarily in agricultural finance. Throughout the 1930s, while at the University of California-Berkeley and Harvard University, he published a series of papers on banking reform, the Federal Land Banks, agricultural stability, and the newly minted Farm Credit Administration. These papers are an interesting read with uncommon foresight, intellect, and ingenuity, and are also the focus of this essay.

Calum G. Turvey is the W. I. Myers Professor of Agricultural Finance, Department of Applied Economics and Management, Cornell University, and editor of the *Agricultural Finance Review*. This essay is part of an occasional review of the history and people that shaped agricultural finance as an academic discipline and as an institution. This paper is based largely on the background material published in Galbraith's memoirs as well as the four papers discussed in the text. Although it has not been through a formal peer review, the paper was kindly reviewed by Bruce Sherrick, Gabriel Power, and Harry De Gorter. Any errors, omissions, or misinterpretations are the sole responsibility of the author.

John Kenneth Galbraith, 1967
[File photo, Harvard News Office: http://www.news.harvard.edu/gazette/2006/05.04/30-galbphotos.html]

That is to say, while the title of this essay says "biography," it is quite meager in its presentation as such, and should be viewed as no more than a brief sketch of Galbraith's career over a four-year period between 1934 and 1937 when his academic life was centrally focused on farm policy and agricultural finance.

Although at times fanciful, Galbraith's ideas about agricultural finance were not shallow. He grasped the minutiae of legislative authority, congressional conflict, and historical significance. Indeed, his

papers provide a contemporaneous view of the structures of agricultural finance and the agricultural economy as they evolved in the 1930s. But we should also keep in mind that over this period Galbraith was only between 26 and 29 years old. We get an early glimpse of the wit, prose, and idealization of economics and public policy that ultimately became part of his life's signature for the next 70 years. We also get a foretaste of problems and solutions from Galbraith that while long forgotten to our discipline have reemerged in the present day, including the efficiency of the banking/Farm Credit System, the balance between business and financial risk, cash constraints on the farm enterprise, farm income stabilization, precautionary savings, accounting standards and reporting, regional diversity, land valuation and speculation, business cycles, and risk management.

Galbraith's interest in agricultural finance and farm management was fostered in Canada. A Scottish-Canadian, Galbraith was reared in Elgin County, Ontario, on a 150-acre farm raising purebred shorthorn cattle. Although born in Canada (Iona Station in 1908), Galbraith held true to his Scottish roots—attributing his intellect to the Galbraith clan and his ethic to working the land.

In 1926, Galbraith attended the Ontario Agricultural College (OAC, now the University of Guelph), graduating in 1931. His life at the college was in a state of perpetual sobriety for fear of the devil, languishing first in the toil of the anti-intellectual study of animal husbandry and transferring to the study of agricultural economics at the onset of the great depression.

He once described the OAC to a Toronto magazine as an "academic slum." As a center of scholarly effort, OAC, he claimed, had grave defects and few merits, and it was there that he first began to doubt the competence of economists. Later, when being introduced as one of the University of Guelph's most distinguished graduates, Galbraith, who was to receive an honorary doctorate, retorted with obvious jest that he was its *only* distinguished graduate.[1]

Nonetheless, it was there that his interest in agricultural finance and farm management was piqued. His first research experience in the summer of 1930 involved a study of land tenancy in Ontario, and his first display of public wit appeared at the Canadian National Exhibition (Toronto) in 1930, with a farm management presentation headlined by a sign reading "Running a Farm Without Books Is Like Running a Clock Without a Hand."

In 1931, Galbraith attended the University of California at Berkeley to study agricultural economics where he taught a range of courses from economics to farm accounting while preparing a dissertation on expenditures in California counties. But here Galbraith gained more than a dissertation as he fell under the influence of the liberal mindset so pervasive in California at the time. As a research assistant, Galbraith worked with E. C. Voorhies to improve the economic position of the California bee industry. But he did publish as a graduate student and in 1934, at age 26, following a brief summer interlude with the Agricultural Adjustment Administration (AAA), he was offered a lectureship at Harvard University.[2]

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[1] These stories of Galbraith's years at the Ontario Agricultural College have gained strange affection at the University of Guelph. As a Scottish-Canadian, trained in agricultural economics at the University of Guelph, and a former faculty member, I can attest that the academic bar at the University of Guelph has risen since 1928. In 2006, it was ranked as the top comprehensive university in Canada by *McLean's Magazine*.

[2] Working for the AAA, Galbraith was asked to come up with a policy on agricultural land on which farmers were either unwilling or unable to pay taxes. He proposed such land be purchased for the price of unpaid taxes and owned by the public. The policy was not entirely ignored, but neither was it implemented as proposed. Nonetheless, the proposal was a foreshadowing of Galbraith's view that government should not be a silent partner in public policy but an active one working for the public good.

There are four papers of particular interest written by Galbraith in the 1930s that dealt with the early development of the Farm Credit System, farm policy, Production Credit Associations, and banking. The first, published in the *Journal of Farm Economics* in 1934, investigated the impact of branch banking on agricultural and rural credit. The second (co-authored with J. D. Black), published in the *American Economic Review* in 1936, examined the emergence and structure of the Production Credit Associations as they evolved following the 1933 Act. The third, published in the *Journal of Farm Economics* in February 1937, examined the policies of the Farm Credit System and the Land Banks, and the fourth (co-authored with R. M. Macy and W. Malenbaum) in the *Journal of Farm Economics*, December 1937, examined existing lending policies and how they affected farm stability.

Galbraith on Branch Banking

The first paper that Galbraith published, "Branch Banking and Its Bearing on Agricultural Credit," appeared in the *Journal of Farm Economics* in 1934 while Galbraith was still a graduate student at Berkeley. His concern was for the potential impacts of the Glass-Steagal Act or the Banking Act of 1933 on the agricultural economy. The Act permitted national banks to enter into statewide branch-banking in those states that permitted branch-banking for banks holding State charters. The purpose of the Act was to loosen the restrictions imposed on nationally chartered banks to allow them to take over state banks in the turmoil of the depression.

Galbraith's concern here was that a banking system, which at the time was more or less in a pseudo-decentralized state, could upon full decentralization impact the country banks. Galbraith was also motivated by his observation that the agricultural economy showed, in general, an antipathy toward branch banking in favor of unit banking.

Galbraith made the case that good performance for any banking system included: (*a*) making a satisfactory distribution of credit between the various groups of borrowers, (*b*) the provision of banking facilities which combine convenience with reasonable cost to borrowers or lending groups, (*c*) equitable treatment of the interests of depositors and borrowers, and (*d*) accomplishing the process with the maximum of efficiency and safety and a minimum of exploitation (p. 222). For the farmer, a reasonable conjecture was the need of a banking system that would provide an adequate supply of credit combined with economy in the interest rate applied, and a certainty in, or constancy of, credit supply year over year. It was in the provision of these services that Galbraith evaluated the pros and cons of branch banking relative to the unit bank.

One of the largest concerns from the point of view of the local country bank was that the branch banking system would siphon off funds from rural areas to urban areas. Galbraith argued to the contrary, noting that many of the country banks placed deposits into the urban banks, and as such the urban banks did not by location constitute areas of deficit funding. Indeed, the urban areas were almost always areas of surplus funds and consequently were better positioned to reallocate loanable funds to deficit areas. But Galbraith also challenged the argument that local supply of funds was limited to a scatter of deposits. If deposits were not sufficient to meet loan demand, there were alternatives such as the mortgages through the Land Banks, credit from the Federal Reserve Banks, the formation of Production Credit Associations, and the emergence of the Farm Credit Administration.

Whatever arguments were made to indicate rural credit deficits, these were in 1933/1934 being usurped by institutional supplies of credit. Nonetheless, in terms of bank credit, the adequacy of funds would more likely increase with branch banking as the pool of loanable funds could be more efficiently and economically

distributed to rural communities which were not at the time well integrated as a system for rural finance.

Perhaps more salient was the sociology of banking. Branch banking by its very nature had to be institutionalized, managed to gain efficiencies, and operate as a whole to manage its parts. This, it was feared, would bring about a coolness and impersonal form of banking, with a branch bank being less tied to the community than the unit bank. But frugal lending bode well with the frugal times of the 1930s, and all too often the spirit of community cooperation and personal identification led to loans that would not have otherwise been made. Indeed, to a large extent, it was the infrugality of loans at the local level that necessitated not only the Glass-Steagal Act but the Farm Credit Act as well.

Even so, Galbraith recommended that should branch banking take form by acquisition of country banks, the social aspects of banking could largely be preserved if the local staff and management were retained. He was less sympathetic to arguments against more stringent lending policies, arguing instead that the branch bank's focus on credit risk was more economical in the long run than simple earnings.

Relative to cost economies, Galbraith argued the branch bank would more than likely be able to operate at a lower cost than the country bank. This was not so much in terms of the physical facilities of the branch, for it has to be purchased and manned just like the country bank. But efficiencies would still accrue in terms of back office operations, advertising, and the like, and with larger scale across banks (and perhaps economies of scope) the costs of lending would likely be lower. The caveat, of course, was whether these economies would manifest lower loan rates, higher deposit rates, or distributed earnings. In the shorter run, such economies could be used to attract borrowers and lenders to the branch banks, but Galbraith does not suggest that the economies are sufficient to lead to the demise of the country bank where both must coexist and compete.

On the certainty of loan supply, Galbraith argued in favor of the branch bank. The mobility of funds between branches is a key advantage over independent banks. To the branch banks, deposits are fungible. In other words, if one looks at the parent bank's earnings, assets, and liabilities as consolidated from the branches, then it is inconsequential whether a loan is provided at branch A from excess deposits at branch B. The flexibility to move funds from surplus to deficit regions is a key to the mobility and certainty of money. To the independent bank such is not the case. Deposit surpluses can be stored in other banks but these often come at lower deposit rates than for individuals, and therefore storage of surplus funds is not costless. On the other hand, in periods of high demand, deposits may be stretched to the limit, leading to rationing among farmers or even denial of loans to borrowers of good character and quality.

Galbraith made two further points, both in favor of branch banking. First was on the safety of deposits. It is less likely that a branch system can be exploitive or carry on dubious practices than an independent bank. This is important for borrowers but perhaps even more so for depositors who, in the absence of deposit insurance, ran the risk of losing deposits to unscrupulous or careless bankers. The second point was the concept of a "money trust," a new economy in which the powers of the banks could become so great they would lead and control the government. Galbraith dismissed this notion while not excluding the possibility: "In the abstract it may be rightly said that popular government is in a pitiable state if it must keep small or weak that which it fears it cannot control" (p. 231). In other words, even if a sovereign power were to be pressured by powerful lenders, it would through necessity adapt.

Galbraith on the Production Credit System

As noted above, when Galbraith reached Harvard, he was provided funds to investigate the Farm Credit System and rural credit. The first of these papers, written with J. D. Black in 1936, took a critical look at the Production Credit System as it evolved under the New Deal reforms of 1933. Of concern to Galbraith were the competitive structure of the Production Credit System in comparison to commercial lending and the more perplexing problem of how such a system could maintain a consistent cost structure across disparate regions of the agricultural economy. Both problems were related and tied to the rediscounting of notes issued by the 1923 Federal Intermediate Credit Banks. The exasperating conditions of the depression in 1931 caused a sharp drop in the demand for the notes, forcing Congress to appropriate $20 million to recapitalize the Credit Corporations which would in turn discount paper with the Intermediate Credit Banks.

By then, commercial banks and merchants were wary of agriculture and dealer credit was difficult to obtain. These difficulties were reminiscent of the post-World War I recession which restricted production credit to such an extent that the 1923 Agricultural Credit Act was necessitated. Emergency loans for production had been provided since 1921, but more than a stop-gap measure of intervention was required. The Act was not designed to compete with banks; rather, it was a means to capitalize cooperatives and associations to facilitate production credit when other forms of commercial credit could not be obtained.

In terms of the 1933 Act, Galbraith questioned the soundness of the Production Credit Associations as a reasonable substitute for commercial credit. This is not to suggest he questioned the idea of a production system of credit operating in tandem with the mortgage credit provided by the Federal Land Banks (established under the 1916 Federal Farm Loan Act), just its efficiency. In fact, farmers were so accustomed to commercial credit and the federal provisions of emergency loans for agricultural inputs that as of 1931, only one credit association was operated on a permanent basis.

The depression years saw a change in this trend as country banks shied away from risky agricultural credit. Political pressure from farmers unable to purchase production inputs encouraged the 1932 Act which led to the formation of 12 regional Production Credit Banks. The cost of production credit offered by the Production Credit Associations (PCAs) was to be equal across the USA. The Production Credit Associations obtained their funds from the Intermediate Credit Banks which in turn obtained funds from issuing notes or bonds to investors. The initial capital of the PCAs was obtained by an initial share offering from the Production Credit Banks which were also overseers of the process.

What ultimately emerged from the work of Galbraith and Black appears to be the first critical assessment of the Production Credit Associations as enacted by the Production Credit Act (1933). They showed that while credit demand of the PCAs increased between 1933 and 1935, the amounts paled in comparison to commercial credit. According to Galbraith and Black, PCA credit represented by one measure only 1/30th of unsecured credit outstanding and by another only 7.6% of commercial operating credit. Why would the uptake not be more?

As Galbraith and Black argued, the competitive position between the PCAs and the country banks was quite imperfect. First was the issue of loan rates. The PCAs were locked into a fixed margin above the debenture rate obtained by the intermediate credit banks, but there were associated problems. Throughout the depression, there was a moratorium on interest charged on deposits; as market rates varied, the cost of deposits to lenders

did not. Thus country banks could more easily compete on loan rates.

Second were the costs of acquiring and managing the loans. This was more pervasive in the rural South and the Great Plains where distance and poverty made loan application and regularization very costly and often higher than the fixed 4% margin allowed by statute. Galbraith and Black note that in the South, lending rates exceeded 20%, not because of usury, but simply because the costs of making the loan were so high. Commercial banks were not constrained on the loan rates they offered and could therefore lend at rates whereby costs could be recovered. On a fixed margin, however, PCA loans to these areas became prohibitively costly.

Third, the share structure and relationship between the PCAs and the regional Production Credit Banks was such that the Banks would provide 20% of capital (which could be leveraged by a factor of 5 to make loans) and sometimes more (at the behest of the Governor of the FCA), and in return would receive shares in the PCA. Meanwhile, as with the Land Banks, PCA borrowers would have to contribute 5% of loans as paid-in capital to the Association. In theory, receiving stock would create value to the farmers, but in practice, the shares in the Land Banks were viewed as being worthless since no dividends on the shares had ever been made. Regardless of the posted rate, many farmers who were not of the cooperative spirit would simply look at the share requirement as a tax and add on 5% to the posted rate to come up with the effective rate. This effective rate would be much higher than the country bank rate. On the other hand, using equity to capitalize the associations was a low-cost approach to obtaining loan funds, and additional indirect subsidies related to supervision, research, and aid in management would also be to the PCA's advantage. The PCA fixed facilities were generally much lower than the ornate premises of the country banks, and the PCAs did not have the burden of check processing and other service costs required by the commercial banks.

A fourth competitive abstraction was the issue of convenience. The FCA and the Production Credit Banks demanded a lot of the farmer in terms of the application process, and approval of any PCA loans was (at first) not local. Compare this to existing country bank relationships and the convenience of borrowing from an institution that could make same-day loans and would be frequented by farmers for depositing funds into savings or checking accounts. Even in the face of credit rationing and a clear demand for operating credit in the depression-era agricultural economy, it should not have been a surprise that PCA credit barely pierced a share of the credit market.

The Galbraith and Black inquiry into the Production Credit System was at best cursory, as the Act had only been operational for two years. In that time, not only had the entire structure of the FCA been convened, but also the entire structure of the Production Credit Banks. Still, Galbraith leaves one wondering at the end: If production credit was so constrained in the depression years leading up to the New Deal, why was the share of PCA loans so small by 1935?

Galbraith on the Farm Credit System

The second paper of 1937 took a hard and serious look at farm credit in the United States and presented some ideas that are still discussed in a variety of forms today. Co-authored with R. M. Macy and W. Malenbaum, Galbraith raises the issue of amortization which first appeared in the 1916 Federal Farm Loan Act. Galbraith's objection was not so much the concept of amortization but the inflexibility it created when markets were bad, for with it no resolution could come of a failing enterprise.

As an object of reform, amortization replaced the sequential system of short-term loans of the day, extending terms with declining interest and increased principal. However, by 1928, what

advantage had remained of these mortgages when 76% of all mortgages had maturities of five years or less? Furthermore, many of these were not mortgages in the sense of amortization, but notes with lump-sum payments and periodic interest. Renewal at the end of the term was not a foregone conclusion. Only the amortized Federal and Joint Stock Land Banks had maturities of greater than 10 years.

Galbraith's opposition was rooted in the observation (or perhaps belief) that the short-term mortgage encouraged early repayment of loans. He was also concerned about the duration of fixed interest rates of long-term mortgages, arguing instead for the prudence of a rate that would remain more or less in sync with market rates when renewal was more frequent. On the renewal side, Galbraith held that in prosperous times farmers with long-term mortgages had no incentive to increase principal payments beyond what was scheduled, whereas a short-term loan would be paid off quite rapidly if it matured in prosperous times. If it matured in poor times, then the farmer need only pay what was possible and then renegotiate a renewal of the remaining principal at prevailing rates.

In contrast, the long-term Land Bank mortgage held the farmer to a fixed repayment scheme, at rates that could be higher than current rates, and added equity at a much slower rate. This would have been adequate in Galbraith's view if not for the assumption that the farmer throughout the life of the loan would always have a minimum and mathematically predetermined ability to make repayments. It was the inflexibility of any fixed payment regime in times of depression that troubled him.

Certain variants on the theme were presented. One, referred to as the Springfield Plan established a fixed schedule of equal principal payments and as principal was paid off, interest rates would fall. In early years this would be fine if times were prosperous and indeed the plan had a prepayment option allowing for prepayment of principal. These prepayments could then offset deferred payments in poor years and the loan would not be in default as long as the total payments received were equal to or greater than the accumulated scheduled payments. Interest, however, could not be prepaid, and if farmers could not afford the principal, then it was equally likely they could not afford the interest.

To provide flexibility, one of Galbraith's suggestions was to establish a reserve fund into which farmers could deposit funds in prosperous years and on which interest would be earned. In the case of default, funds would be withdrawn from the reserve account, and if default never occurred, then once the accumulated value of the reserve account equaled the mortgage principal, the loan would be repaid. Of course, this would not be very helpful if recession hit before a reserve could be built up, nor would it be attractive to many poor farmers who had little reserve funds above household requirements to contribute. Nor would it be attractive to the well-to-do farmer who might prefer to place excess funds in other investment/reinvestment alternatives.

Another alternative was an automatic or contractual adjustment in accordance with rising or falling farm incomes. Galbraith advocated a flexible loan schedule that would be indexed to farm income (or some other correlated index) so that in prosperous years the farmer would accelerate payments on the loan, and in sour years obligations would be reduced. One unlikely plan, referred to as the "crop share mortgage," would have the lender take a stated proportion or share of the farmer's income each year as payment. Although the Farm Credit Administration toyed with this idea, there were issues of compliance, and in the absence of formal record keeping and accounting, a degree of difficulty in actually determining the correct income from which the share should be extracted.

This left the index plan. Galbraith argued that a national index of farm incomes be constructed and used as the base. As the index rose, then the principal payments would be increased by a stated proportion of the increase; when incomes fell, relief likewise would be provided, but not necessarily to the same proportion as an increase. To this an adjustment would be made using a regional index or commodity index, depending on the client, to account for stronger or weaker income levels than prescribed by the national average and perhaps with adjustments for the cost of living. At any rate, such a proposal satisfied Galbraith's requirement that loan terms were flexible with respect to reducing payments in bad years and contractually accelerating payments in good years.

While such a theme has been repeatedly considered in various forms since 1937, there is one notable lapse in Galbraith's argument, and this is the duration effect. If the adjustable mortgage or indexed mortgages worked in practice, then this would mean that once per year when the indexed payment was announced the duration of the loan would have to be recalculated. For example, a sequence of three bad years could extend a 10-year mortgage to 14 or 15 years, or a sequence of three good years could reduce the life of a 10-year mortgage to six or seven years or less. In other words, the transference of repayment risk on a fixed-term mortgage to a no-default mechanism simply transfers that uncertainty to the duration of the loan.

This gives way to the competing interests of the farmer who would prefer an ability to repay a loan quickly to reduce total interest expenditures versus those of the lender who might prefer longer duration loans in order to maintain a longer stream of interest revenue. But then perhaps Galbraith did not ignore this problem; rather, he might not have cared. Earlier in the manuscript, Galbraith argued in favor of the perpetual mortgage for non-depreciable assets such as land and the utility it would provide in using the avoided principal payments for alternative investments, reinvestment in land, equity build-up, and inter-generational transfer. To Galbraith, any process that would match the terms of repayment to farm liquidity was an improvement over the inflexibility of fixed-term amortization payments.

Galbraith and the Federal Land Banks

The last paper in the Harvard trilogy was published in the proceedings issue of the *Journal of Farm Economics* in February 1937. What is interesting about this paper is that Galbraith had as a discussant F. F. Hill who was soon to be Governor of the FCA, having been brought to Washington from Cornell University by W. I. Myers. One would think it a rather daunting task at the age of only 28, and not yet secured in a tenured position, to go up against such formidable might, but it unlikely fazed Galbraith. Hill, on the other hand, was unimpressed—as will be discussed below.

In his article "The Federal Land Banks and Agricultural Stability," here again Galbraith played the role of futurist under a number of assumptions including that in the short run (as at 1937) prices would eventually rise above 1929 levels, but from time to time depression would hit the agricultural economy. With these ideas in mind, he set forth a discussion of how policies of the Federal Land Banks could promote stability or instability of the farm enterprise.

By stability, Galbraith was referring to the increased risks that emerge with the fixities of financial leverage (financial risk) when commodity markets are uncertain (business risk). To this end, Galbraith asserted there was little the banks could do to affect markets and prices, but there was much they could do to stabilize the farm economy. Stabilization would include actions taken before a recession/depression occurred as well as those that could be taken during a depression by

reducing mortgage charges, refinancing, preventing disclosures, and withholding foreclosed property from the market.

Galbraith at this time was very much concerned with land prices and speculation, and once again he proposed frugality. Land Banks, he claimed, must discriminate between the demand for economic rents and the demand for gain, the latter forcing land prices to well exceed the fundamental value implied by the former. We must, of course, keep in mind that Galbraith's economic views were based on the hand that was dealt at the time, including an odd approach to farm lending which established loan amounts as a percentage of the "normal" price of land based on pre-war (1909–1914) prices. To Galbraith, this satisfied the principle of frugality—perhaps not in the Scottish-Canadian sense of frugality which stereotyped his heritage, but in the sense of sound financial policy.

It may be that Galbraith was playing wunderkind with a bit of Keynes (whose treatise was published in 1936) who suggested that in times of rising income, money supply should be tightened. So, too, for land prices Galbraith reasoned. By indexing land to pre-war prices, there was little correspondence between the normal price and the appraised market price. This weeded out those who would not have been able to support the land on one hand, while restricting access to debt for those who merely wanted to speculate. Of course, this would not apply in a downturn—for who would speculate in such a market?

While Galbraith saw the pre-war indexing of land by the Land Banks as a stabilizing force, he took umbrage at the so-called Commissioner's loans. A Commissioner's loan was normally taken as a second mortgage and with it a farmer could borrow up to 75% of the appraised value of the land. So popular were Commissioner's loans that in 1935 about 44% of all mortgages were Commissioner's loans. Consequently, while the Land Bank policies provided stability through frugal polices of lending to what amounted to no more than 50% of the appraised value of the property, the Commissioner's loans created instability through increased leverage and speculation. Indeed, Galbraith (footnote 4, p. 56) suggested appraisals be done away with completely and the job of appraiser be confined to repayment capacity calculations from which a realistic loan amount could be established. In other words, Galbraith, as early as 1937, was warning against the use of market valuation and capital gains in loan determination in favor of operational cash flow after living expenses.

Galbraith was also concerned with policies in place throughout the mid-1930s that while designed to assist farmers could hamper recovery. He repeated his concerns about the instability of amortization payments. Regular amortization payments on Land Bank loans were deferred until 1938, and principal on all Commissioner's loans were deferred for a period of three years. If those years happened to be years of economic recovery, there was little the lenders could do to promote payment of principal, but if the principal was demanded during a downturn, the outcome, despite the good intentions of the policy, could be devastating.

In fact, Galbraith suggested an altogether different policy based upon the theory of precaution and countercyclicity. Under this proposal, the lenders should demand advance payment of principal during periods of recovery (as opposed to the voluntary repayment policy encouraged by the FCA). This would ensure a balance of payment while building equity in good years and providing the flexibility for lower payments in the lean years.

A countercyclical proposal for interest rates was also discussed. According to Galbraith, interest rates should rise during recovery, reducing demand and access for credit and mitigating or slowing the effect that access to credit has on land prices and speculation. In other words, Galbraith was proposing a form of credit rationing in times of prosperity to slow growth.

On the other hand, the increased interest rates would remain during a downturn, resulting in an unfortunate transfer of the land base between those with existing high interest rates and those who could acquire loans at lower rates. But this was unacceptable because it promoted instability. Instead Galbraith considered a compromise in which rates would increase to no more than competitive market rates during recovery, while being lowered during downturns. Presumably the compromise was a variable-rate amortization loan which eliminated the fixity in contract rates across good and bad times.

Finally, Galbraith offered (for consideration rather than recommendation) the possibility that the Land Banks and the Farm Credit Administration take on the role of overseer of the farm mortgage market including private lenders. From such a vantage point, the system as a whole could monitor the lending policies of private lenders including issues of foreclosure, and engage in supply management of agricultural land. On this latter point, Galbraith suggested the Land Banks could use their considerable holdings of farm land to supply more land when land prices are rising or becoming too speculative, while withholding land from the markets to suppress depression in land prices. Galbraith admits that such a role would be incompatible with the ultimate goal of the Farm Credit System being a borrower-owned and controlled cooperative, as envisioned by FCA Governor W. I. Myers. Again, however, Galbraith's essay was not to force recommendations but to examine means by which the system as a whole either contributed to, or could take actions to mitigate, instability.

In responding to Galbraith, Forrest Hill commented that to follow the proposals would be tantamount to reorganizing the system as a government controlled and operated farm mortgage system. To Hill, Galbraith's proposal would have required a substantial decrease in the bond-to-capital ratio of the system. For example, holders of the bonds used to finance the system have a normal expectation of periodic and constant payments. These could not be sustained if interest rates were not allowed to vary with the market, principal payments were not constant, or default* risk was curtailed through foreclosure policies.

Additionally, such proposals were broad sweeping, when many of the problems facing the system at the time were based on individual situations that were not altogether common across borrowers. In short, Hill agreed that the problem of agricultural stability was a worthy one, but unless the Farm Credit System could control the activities of private lenders such lofty goals were probably not attainable. And perhaps what Galbraith did not understand at the time was that the USDA was already mounting an effort in 1937 to absorb the Farm Credit System as a division of the USDA.

1937 and Beyond

Beyond 1937, Galbraith wrote less and less about agricultural finance or economics, as the influence of Keynes pushed away Marshall's view of well-behaved consumers, producers, and government. He was also influenced by Thorstein Veblen's (who died in 1929) willingness to challenge the conventional wisdom and to challenge the neoclassical Marshallian model as something of a humbug by its introduction of decadence and conspicuous consumption.

Furthermore, although he had been promoted to faculty lecturer at Harvard in 1937, Galbraith took on a post-doctoral position at the University of Cambridge where macroeconomics and public policy took hold. By 1939, he had returned to the United States and accepted a position at Princeton University, but that was short lived. His last formal occupancy as an agricultural economist was a position he accepted in 1940 as the first agricultural economist hired by the American Farm Bureau Federation. This is not to say that

Galbraith's short career as an agricultural economist (by practice, not training) was entirely focused on agricultural finance, as it was not.

In 1954, he published "Economic Preconceptions and the Farm Policy," which is a clever rant against then Secretary of Agriculture Ezra Taft Benson and his open opposition to the shallow but effective commitments of the presidential candidates Eisenhower and Dewey in the 1952 presidential elections. The issue at hand was the price support guarantees at 90% of parity for major grains and oilseeds, which was opposed by virtually all agricultural economists and the major farm unions.

That Galbraith would challenge such thinking is no surprise since it was Galbraith who had instituted the guarantees' precursors as the chief architect of price controls during the second world war. But it was audacious nonetheless. The conventional wisdom of post-war welfare economics, as led by Theodore Shultz, suggested a very grave agricultural economy—one that was infirmed and inefficient from an inability of resources to adjust to real and relative prices, with consequential trade impacts, and the challenges that such polices would pose for the freedom of choice, political independence, and moral character of the farmer. Galbraith, in typical liberal style, argued that in fact not all things about price stabilization were bad and asserted it was highly unlikely that the mere existence of price support would not on its own provide the backdrop for a communist overthrow of American democracy.

The last word on agricultural finance (that I could find at any rate) came about in a 1946 review of Earl L. Butz's *The Production Credit System for Farmers*. Proving that agricultural economists could, despite the odds against it, have a sense of humor, Galbraith starts off his review by stating, "This is not a very good book, although it is not a very bad one." He then concludes with, "At the risk of singling out Butz and the Brookings editors from a notable list of offenders, I would like to register another objection to the book. The subject matter is simple, but the language is pretentious and obscure"... [why use] "Realistically speaking it will be politically difficult to promulgate contract interest rates which vary geographically"... [when one can use] "Congress will object if one part of the country is charged a higher interest rate than another."

Galbraith, of course, was himself well known for using language that was both pretentious and obscure. For example, on the 12th line in his words of acknowledgment in his 1982 memoirs, *A Life in Our Times*, Galbraith uses the word "verisimilitude," on page 20 the word "adumbrated," and on page 86 the word "prestidigitation" (as in "I had come up with a somewhat questionable piece of prestidigitation").

Galbraith went on to one of the most successful careers of any 20th century economist. An abiding liberal, he never relinquished his belief in government as the steward of society, a provider of stability. Galbraith's study of Keynes landed him in Washington as administrator of price supports or post-war reconstruction, an advisor to Presidents, editor of *Fortune Magazine*, a distinguished and long-lived career at Harvard, President of the American Economics Society, Ambassador to India, and author.

His writing was prolific, and in 1958 he published *The Affluent Society* (Mentor Books, NY), followed by *The New Industrial State* in 1967 (Mentor Books, NY). He wrote much more, including *The Great Crash, 1929* (Penguin Books, NY, 1954), *Annals of an Abiding Liberal* (Meridian Books, NY, 1979), *The Anatomy of Power* (Houghton Mifflin, Boston, 1983), *Economics, Peace, and Laughter* (Meridian Books, NY, 1971), to mention just a few.

So varied were his interests, expansive his knowledge, principled his beliefs, and protean his experience that his life's descriptor remains an enigma.

But perhaps, beyond his earliest years as a student and scholar of agricultural finance, an apt descriptor is found on the cover flap of an anthology titled *The Galbraith Reader* (Gambit Publishers, 1977), which reads:

> *... the Ontario farmboy as agricultural economist, the agriculturalist as Federal Administrator, the Administrator of Price Controls as civilian military strategist, the strategist as economic theorist, the theorist as political activist, the activist as ambassador, the ambassador as presidential advisor, the advisor as novelist, satirist and humorist, the humorist as philosopher, and the philosopher as part-time farmer once more.*

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Factors Affecting the Agricultural Loan Decision-Making Process

Allen M. Featherstone, Christine A. Wilson, Terry L. Kastens, and John D. Jones

Abstract

Agricultural lenders in today's environment face many challenges when evaluating the creditworthiness of farm borrowers. To address these challenges, a survey was conducted with financial institutions in Kansas and Indiana where agricultural lenders were asked for their responses to hypothetical agricultural loan requests. Each loan request differed by the borrower's character, financial record keeping, productive standing, Fair Isaac credit bureau score, and credit risk. Lenders provided information about themselves and their financial institutions. The survey data obtained determine the relative importance of financial and nonfinancial information when analyzing agricultural loan applications. Tobit models are estimated to identify the borrower and lender characteristics that are important in determining loan approval, while OLS models are used to investigate the factors that affect interest rates offered to farm borrowers. The results offer a comparison of agricultural lending between two important agricultural states and provide lenders with insight on the factors that influence the decision-making process of other agricultural lenders.

Key words: agricultural loans, credit bureau score, credit evaluation, interest rates

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The challenges agricultural lenders face when evaluating the creditworthiness of farm borrowers have dramatically changed over the last several decades. During the mid-1980s, American agriculture suffered through times similar to those of the 1920s and 1930s, again demonstrating the consequences of relying on collateral values supported by inflationary expectations rather than cash flows (Featherstone and Baker, 1987). As a result, many lenders adopted methods that more accurately measure the financial position of agricultural producers, such as credit bureau scores.

Many studies have examined the methods used by lenders without achieving a consensus as to which quantitative and qualitative factors are most important in the agricultural loan decision-making process. In this study, data from a survey administered to financial institutions in Kansas and Indiana are used to investigate the agricultural lending process. The primary objective is to analyze the factors financial institutions consider when lending to farm borrowers. The specific objectives are to: (*a*) determine the relative importance of financial and nonfinancial information when analyzing agricultural loan applications, and (*b*) identify the borrower and lender characteristics important in determining loan approval and interest rates.

Credit Evaluation

According to Gustafson (1989), agricultural lenders use the five C's of credit (capacity, capital, collateral, character, and conditions) when evaluating an agricultural loan application. Gustafson states that

lenders judge these attributes using information obtained from previous experience with a borrower in conjunction with financial statements, references, and other documentation. An individual lender or committee decides whether a borrower possesses sufficient ability to repay loaned funds. While Gustafson acknowledges developments in credit evaluation, he suggests that research focusing on the interrelationships between management decisions, attributes, and traits which distinguish one farmer's behavior from another could enhance assessment accuracy.

In the early 1990s, Gustafson, Beyer, and Saxowksy (1991) administered a survey to 10 agricultural loan officers in the Red River Valley of southeastern North Dakota and west-central Minnesota to identify information sources, credit evaluation procedures, and lending heuristics used. In the survey, lenders described their methods of credit evaluation and responded to seven hypothetical credit situations. The authors reported that lenders placed significant weight on the borrower's financial information and personal characteristics (honesty, integrity, and production-management ability) when making decisions regarding approval, levels of credit, and need for servicing action.

Ellinger, Splett, and Barry (1992) utilized a survey to examine credit evaluation procedures, risk assessment methods, and credit model consistencies among agricultural banks in Illinois and Iowa. They found that, following the farm financial crisis of the 1980s, lenders used more formal and comprehensive methods to evaluate the creditworthiness of agricultural borrowers. Nearly 60% of the lenders used a credit-scoring model to assist in loan approval, loan pricing, loan monitoring, and evaluation of loan portfolio risks. However, results of their survey indicated a relatively high level of disparity among the systems in use by lenders.

Substantial research on credit risk assessment in agricultural lending has yielded mixed results about which factors to include in the development and validation of credit-scoring models (Barry and Ellinger, 1989; Splett et al., 1994). In the late 1980s, Miller and LaDue (1989) focused on the development of credit-scoring models for dairy farmers by employing measures of farm size, liquidity, solvency, profitability, capital efficiency, and operating efficiency as explanatory variables. Their study utilized 203 dairy loans from an agricultural loan portfolio for a single bank in upstate New York. Using logistic regression, Miller and LaDue concluded that the quality of larger borrowers was predicted by liquidity, profitability, and operating efficiency measures.

Using data from 9,403 loans made by Canada's Farm Credit Corporation, Turvey (1991) conducted a similar study by empirically estimating four alternative credit-scoring models. Liquidity and leverage were found to be strong determinants of default risk, in addition to profitability and efficiency. However, results from further analysis supported the inclusion of both qualitative and quantitative factors when selecting a method to evaluate the creditworthiness of farm borrowers.

Splett et al. (1994) built upon previous studies by employing a joint experience and statistical approach to develop and evaluate credit-scoring models. Experienced lenders from the Sixth Farm Credit District assisted with the development of models that incorporated lender experience, knowledge, and intuition. Financial ratios from the Farm Financial Standards Council (FFSC) were used in combination with other collateral measures to develop experienced term-loan and operating-loan models. The models were estimated using logistic regression to determine the relationship between experience and statistical credit-scoring models. Based on the results, the statistical models were moderately successful in replicating lender behavior and classifying actual loans.

Featherstone, Roessler, and Barry (2006) analyzed the Seventh Farm Credit District's loan portfolio over the period 1995–2002 using repayment capacity, solvency, and liquidity to assess the accuracy of financial performance ratios in determining the expected probability of default. Results from the study showed that the underwriting guidelines in place within the Seventh Farm Credit District were statistically significant in determining the expected probability of default.

Lenders' Responses to Loan Requests

During the late 1960s, Baker (1968) introduced the simulated borrowing method as an alternative for evaluating lender responses to various managerial choices in a farm's financial and production organization. He justified this method by noting that actual loan data are limiting because they are restricted to only approved loans and fail to include marginal loans which may be rejected. By empirically testing lender responses to hypothetical loans, Baker concluded banks and credit associations prefer loans that are: (*a*) self-liquidating and (*b*) asset-generating.

Barry and Willmann (1976) employed the simulated borrowing method to develop the decision elements for a risk-programming model of a representative case farm for the Southern Blacklands of Texas and to survey the credit responses of lenders to contract choices. The authors found that lenders' credit response may modify the producer's contracting plans and his or her rate of income growth.

Sonka, Dixon, and Jones (1980) applied similar methods to assess the impact of the firm's financial structure on its external credit limits for 33 agricultural lenders in east central Illinois. Each loan officer was asked to evaluate and respond to five loan situations which varied by financial stress. In each case, the borrower had recently purchased farmland, and was requesting $60,000 to replace a combine and build grain storage facilities. Lender responses fell into two groups, a conservative group and a liberal group, with respect to the average loan amount approved. Findings also revealed that these two groupings of lenders responded differently to the borrower's financial position and structure.

Barry, Baker, and Sanint (1981) used two different lender surveys to examine the concepts underlying farmers' credit risks and to determine how credit may influence farmers' debt use. The first survey asked 101 unit banks and Production Credit Associations (PCAs) in south central and eastern Texas to respond to a representative farming situation. From this survey, 34 responses included loan limits, interest rates, collateral requirements, and other loan requirements. A second survey, conducted by the Federal Reserve Bank of Chicago, resulted in several hundred responses to farm lending conditions. The authors found that a farmer's credit position was positively correlated with changes in the level of farm income and this correlation was stronger for capital credit than for operating credit. Also, variation in fund availability from rural banks was found to contribute to high credit risks.

During the mid-1980s, Pflueger and Barry (1986) elicited commercial banks' and PCAs' responses to a farmer's use of crop insurance. The 55 lenders in Illinois analyzed two case loan requests containing a farmer biography, description of the Federal Crop Insurance Program, and historic and projected financial statements. Each lender evaluated the case loans in terms of maximum credit limits for operating and capital loans, interest rates, loan maturities, security requirements, and other loan provisions. The results indicated that approximately 60% of lenders responded in a positive manner to a borrower's participation in the Federal Crop Insurance Program. The magnitude of credit responses differed considerably while interest rates and loan maturities stayed about the same.

In a 1993 study, Dixon, Ahrendsen, and Barry formulated a two-equation model with the goals of identifying and estimating the variables that lead banks to charge different interest rates on agricultural loans. They used data from a 1990 survey of 34 commercial banks in western Arkansas responding to four hypothetical agricultural loan requests. Each request, which differed by the borrower's financial strength, consisted of an intermediate-term loan of $150,000 for the construction of two broiler houses and a short-term loan of $95,000 for the purchase of stocker steers. For both loans, interest rates were found to be positively correlated with the bank's loan-to-deposit ratio. Results also indicated that banks facing losses may be more aggressive when pricing loans due to the marginal profitability of the loans.

Bard, Barry, and Ellinger (2000) used a case study to evaluate the influence of changes in the banking industry on the cost and availability of agricultural credit. They asked 1,064 commercial banks in Illinois, Iowa, and Indiana to respond to case loans for two of three hypothetical farm borrowers with different demographic characteristics and credit needs. After analyzing the data from the 114 responding banks, Bard, Barry, and Ellinger found no overwhelming evidence in support of or against commercial bank consolidation as it affects agricultural lending. Thus, results suggest that other nonmeasured factors influence the loan terms offered by commercial banks to agricultural borrowers.

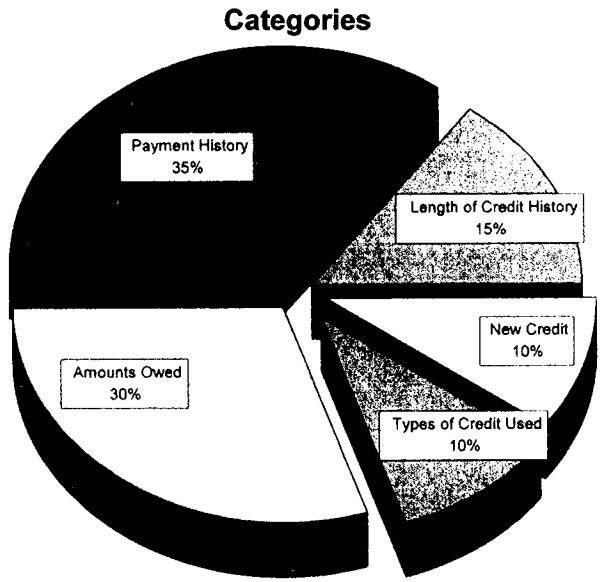
The number of studies examining the agricultural lending decision provides strong evidence that lenders consider both financial and nonfinancial variables when evaluating the creditworthiness of farm borrowers. However, various credit evaluation procedures and methods have been studied without achieving a consensus as to which variable measures should be used when analyzing agricultural loan applications. Furthermore, while many studies have been conducted, the majority of them do not explicitly consider how lenders use credit bureau scores when lending to farm borrowers. Thus, further research pertaining to the lender's assessment, especially as it relates to the agricultural loan decision-making process, is needed.

Credit Bureau Reports and Scores

An important component of the decision-making process for loan analysis is credit bureau reports. A credit bureau report is a detailed account of an individual's credit history (Fair Isaac Corporation, 2005). A credit bureau or credit-reporting agency maintains files on millions of borrowers containing information collected from lenders, creditors, insurers, and employers. The three major credit bureaus, Equifax, Experian, and TransUnion, all provide credit bureau reports.

The typical credit bureau report includes four categories of information. The first category contains personal or identifying information including the individual's name, current and previous addresses, telephone number, social security number, date of birth, and current and previous employers. The second category outlines the individual's credit history, providing specific details about credit accounts and loans, including late payments, skipped payments, accounts turned over to collection agencies, and repossessions. The third category contains public record information from local, state, and federal courts, and information on overdue debt from collection agencies. Public record information includes bankruptcies, foreclosures, suits, wage attachments, liens, and judgments (Fair Isaac Corporation, 2005).

Inquiries are the last category of information in a credit bureau report. This includes a list of everyone who has voluntarily or involuntarily accessed credit bureau reports on the individual within the last two years. Voluntary inquiries are initiated by the individual for obtaining credit, while involuntary inquiries are



Source: Fair Isaac Corporation, 2005 (http://www.myfico.com).

Figure 1. Categories Used in Determining a Fair Isaac Credit Bureau Score

situations where lenders have accessed and reviewed the credit bureau report for preapproved credit offers. Although both inquiry types are part of a credit bureau report, involuntary inquiries do not appear on the credit bureau report received by a lender.

Along with a credit bureau report, lenders can also purchase a credit score from each of the credit reporting agencies. The score in the credit bureau report is calculated using a formula developed by the Fair Isaac Corporation (FICO). Although the specific relationship is unpublished, there are five basic factors used in determining a credit score (Figure 1).

Since lenders and other credit grantors may not report account activity to all credit bureaus, an individual's credit score may vary among the three credit bureaus. Credit scores range from 400 to 900, with the average around 700. According to the scoring model, as an individual's score increases, his or her risk of default decreases.

Experimental Design

Survey Methodology and Instrument

The primary objective of this study is to analyze the factors considered by financial institutions when lending to farm borrowers. To obtain the required data, the hypothetical borrowing approach is used. The basics of this method include conducting a simulated borrowing experiment through a mail survey to elicit lenders' responses to hypothetical agricultural loan requests. The survey was conducted in Kansas and Indiana.

The survey instrument is a combination of hypothetical agricultural loan requests and a survey questionnaire. Each loan request consists of four sections: (*a*) farmer scenario, (*b*) borrower's financials, (*c*) ratio analysis, and (*d*) the agricultural lending decision. The farmer scenario section provides a biographical sketch of the individual farmer and presents his request for funds to purchase an additional tractor.

Kansas and Indiana have a number of farms that are comparable in size and value of sales. Although Kansas has more livestock enterprises, both states have a large number of agricultural operations that are involved in the production of grain and oilseeds.

The borrower's financial section includes accounting information from the balance sheet, income statement, and cash flow statement for the years ending December 31, 2002 through 2004. The ratio analysis section contains financial measures of liquidity, solvency, profitability, repayment capacity, and financial efficiency. Finally, the agricultural lending decision section presents a variety of questions concerning the agricultural loan decision-making process, including the decision the borrower would receive from the lender's financial institution.

The second component of the survey instrument is a one-page questionnaire consisting of two sections: bank characteristics and loan officer characteristics. The bank characteristics section focuses on descriptive factors about the financial institution. Such factors include bank size, portfolio composition, profitability, lending risk, and location. *ASSETSIZ* is the total asset size of the bank (billions of dollars), *CA* is the bank's ratio of capital to assets (percent), *ALTL* is the bank's ratio of agricultural loans to total loans (percent), *ROA* is the bank's return on assets (percent), *LNDE* is the bank's ratio of loans to deposits (percent), and *NCLTL* is the bank's ratio of noncurrent loans to total loans (percent).

The section on loan officer characteristics requests information about the responding lender's degree of involvement in agricultural lending, his or her individual lending authority, and decision-making authority. *EXP* is the number of years of lending experience the loan officer has as an agricultural loan officer (years), *PTIME* is the percentage of time the loan officer spends on agricultural loans (percent), and *MLA* is the loan officer's maximum individual lending authority (dollars).

Survey Design

A total of 144 hypothetical agricultural loan scenarios were created. For each of the 144 scenarios, the personal and business information as well as the loan request (amount and purpose) are the same, with the exception of the farmer's name. Conversely, the farmer attributes vary by the borrower's character, financial record keeping, productive standing, credit risk, and Fair Isaac credit bureau score. The information provided to the lender is much the same across alternative loan requests to minimize the review time required by the lender while maximizing the information provided.[1]

Another step in designing the survey instrument consists of preparing key financial statements that match with the credit risk ratings. Two sources of data—the Kansas Farm Management Association (KFMA) Annual Whole-Farm and Enterprise Summaries and the USDA's 2002 Census of Agriculture from Kansas and Indiana—were used to create four sets of financial statements. Financial measures of liquidity, solvency, profitability, repayment capacity, and financial efficiency were calculated in accordance with the recommendations of the Farm Financial Standards Council (FFSC).

The expected probability of default (credit risk) is calculated for each of the sets of variables using the credit-scoring model defined in Featherstone, Roessler, and Barry (2006). To determine the probability of default, first determine the log odds ratio:

$$(1)\quad \mathrm{Ln}\left(\frac{\textit{Probability of Default}}{1 - \textit{Probability of Default}}\right) = -2.3643 - 0.00135(RC) - 0.0217(OE) - 0.00399(WC),$$

where *RC* is the repayment capacity percentage, *OE* is the owner equity

[1] See Jones (2005) for a copy of the survey instrument and the accompanying information provided to the lender.

Table 1. Expected Probability of Default for Each Credit Risk Variable

	Credit Risk Levels			
Year	1	2	3	4
	(%)			
2002	6.98	3.69	1.54	0.86
2003	7.18	3.80	1.61	0.88
2004	7.61	3.68	1.48	0.74

percentage, and *WC* is the working capital percentage. Next, calculate the expected probability of default:

$$(2)\quad \textit{Probability of Default} = \frac{e^{xb}}{1 + e^{xb}},$$

where *xb* is the result of equation (1)'s right-hand side. Table 1 reports the expected probability of default for each credit risk variable with respect to year. These four scenarios are consistent with the distribution of credit ratings reported by Haverkamp (2003) who found that 90% of the observations of credit ratings for Kansas farms were in this range.

Survey Process

Following a pretest and approval process, a systematic method selected the loan requests and assigned them to the lender (Table 2). The Excel RANDBETWEEN function chose a random number between 1 and 144 which corresponded to a hypothetical agricultural loan request. Blocking and replication methods ensured the probability of receiving a specific loan request remains constant across the scenarios given to each lender. In situations where duplicate scenarios occurred, new scenarios were generated and reassigned to the lender.

An Excel macro was created to produce a database containing information on 10,016 hypothetical agricultural loan requests. The loan application packages for the sample lenders included a cover letter, four loan requests, one questionnaire, and a business reply envelope.

Table 2. Systematic Method for Selecting Loan Requests

Lender	Loan 1	Loan 2	Loan 3	Loan 4
1	7	39	49	24
2	107	6	69	136
3	56	53	17	38
4	40	1	27	124
5	106	14	46	109
⋮	⋮	⋮	⋮	⋮
2,502	119	1	9	70

Lending Factors and Levels

A key issue in examining the factors considered by financial institutions in production agriculture lending is to identify the sources of variation. The factors of interest to this study were character, Fair Isaac credit bureau score, financial record keeping, productive standing, and credit risk. Levels for each of these factors were defined as follows.

- Character (*CHAR*) is a qualitative nonfinancial variable that encompasses personal factors such as honesty, integrity, and reliability. The borrower's character is defined by two levels: honest or dishonest. The borrower is considered honest if the lender visited with a number of individuals in the agricultural community and they all confirmed that the farmer was honest in his business dealings. The borrower is classified as dishonest if three of the individuals in the agricultural community expressed concerns regarding fairness in business transactions with the farmer. *CHAR* = 1 if the individual is defined as honest and 0 if the individual is classified as dishonest.

- Fair Isaac Credit Bureau Score (*FICO*) is a quantitative nonfinancial variable that provides an indication of the borrower's financial integrity. A Fair Isaac credit bureau score of 725 represents a low-risk borrower, while a score of 560 represents a high-risk borrower. *FICO* = 1 if the farmer has a Fair Isaac

credit bureau score of 725 points and 0 if the farmer has a score of 560 points.

- Financial Record Keeping (*EXCFRK*, *AVGFRK*) is a qualitative nonfinancial variable representing the borrower's ability to maintain complete and accurate up-to-date records. This includes borrowers who keep their own records by using computerized applications, or other innovations for farm accounting and financial management purposes. This also includes borrowers who employ an accountant or record service to provide computerized record keeping, whole-farm and enterprise analysis, and tax preparation. A distinction is not made between these two forms of financial recording keeping. In this study, the borrower's financial record keeping ability is defined as excellent, average, or poor. *EXCFRK* = 1 if the observation corresponds to a scenario where the farmer is an excellent financial record keeper and 0 otherwise. *AVGFRK* = 1 if the observation corresponds to a scenario where the farmer is an average financial record keeper and 0 otherwise. The default category is a poor record keeper.

- Productive Standing (*PSUPQ*, *PSMID*) is a qualitative nonfinancial variable that refers to the borrower's ability to manage business risk, select appropriate production and marketing activities, and meet realistic price and yield assumptions. Three levels—upper quartile, middle-half, and lower quartile—are used to define the productive standing. Each level provides a measure of how the borrower's operation ranks in comparison to other industry participants. *PSUPQ* = 1 if the observation corresponds to a scenario where the operation ranks in the upper quartile and 0 otherwise. *PSMID* = 1 if the observation corresponds to a scenario where the operation ranks in the middle and 0 otherwise. The default category represents a producer in the lower quartile.

- Credit Risk (*CR*) is a quantitative financial variable which consists of the borrower's financials and ratio analysis. The borrower's financials include three years of selected accounting information from the balance sheet, income statement, and cash flow statement, while the ratio analysis contains financial measures of liquidity, solvency, profitability, repayment capacity, and financial efficiency. In this study, the borrower's credit risk is represented by four levels. *CR* = 7.61 if the observation corresponds to a scenario where the expected probability of default is 7.61%, *CR* = 3.68 if the observation corresponds to a scenario where the expected probability of default is 3.68%, *CR* = 1.48 if the observation corresponds to a scenario where the expected probability of default is 1.48%, and *CR* = 0.74 if the observation corresponds to a scenario where the expected probability of default is 0.74%. Alternatively, *CR*1, *CR*2, *CR*3, and *CR*4 are equal to 1 if the probability of default is 7.61%, 3.68%, 1.48%, and 0.74%, respectively, and equal to 0 otherwise.

The full factorial design, which is the total combination of these factors and their levels, results in the 144 (2 × 2 × 3 × 3 × 4) combinations of hypothetical agricultural loans. Each combination represents a farmer scenario coded by assigning one of the most common names that occurred during the 1990 United States Census. As examples, Figure 2 summarizes four of the 144 possible combinations of the loan requests. Lenders analyzed and responded to four systematically selected loan requests by providing the loan amount, interest rate, and terms that they would offer to each borrower. The loan amount and interest rate represent the response variables and are dependent variables used in the analysis. The variable L_t is the proportion of the tractor loan granted, and R_t is the interest rate charged by the financial institution if the loan is approved (percent).

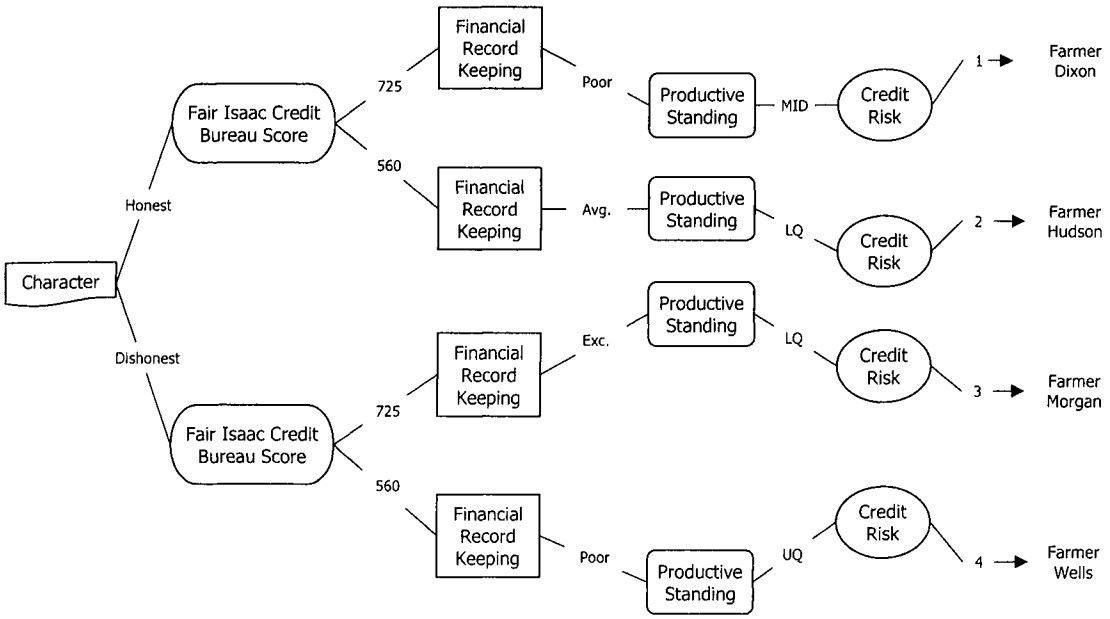


Figure 2. Hypothetical Agricultural Loan Requests

Financial Institution Population and Sample

The Federal Deposit Insurance Corporation (FDIC) website shows that 3,270 commercial banks in the United States had at least $1 million in agricultural loans outstanding as of December 31, 2004. In Kansas, 277 U.S. commercial banks with 978 lending offices, and in Indiana 100 U.S. commercial banks with 1,471 lending offices were selected. Additionally, all Farm Credit offices in Kansas (27) and Indiana (28) were included in the sample. The survey was mailed to 277 commercial banks and 27 Farm Credit offices in Kansas during the week of April 18, 2005. A similar survey was mailed to 100 commercial banks and 28 Farm Credit offices in Indiana during the week of May 13, 2005.

Empirical Models

Loan Amount

In this study, a two-limit Tobit model is estimated because the dependent variable is constrained by the minimum (0) and maximum (1) portion of the loan request that a borrower may receive. The observed dependent variable L_i is determined as follows:

$$(3)\quad L_i = \begin{cases} 0 & \text{if } L_i^* = \boldsymbol{\beta}'\mathbf{X}_i + \varepsilon_i \le 0, \\ L_i^* & \text{if } 0 < \boldsymbol{\beta}'\mathbf{X}_i + \varepsilon_i < 1, \\ 1 & \text{if } L_i^* = \boldsymbol{\beta}'\mathbf{X}_i + \varepsilon_i \ge 1, \end{cases}$$

where L_i^* is a latent variable, $\boldsymbol{\beta}'$ is a vector of the slope coefficients for the matrix of $\mathbf{X}_i$ parameters, and ε_i is the error term.

In the first two-limit Tobit model estimated for the tractor loan amount granted, the variables *CR*3 and *CR*4 are included to represent the credit risk or expected probability of default corresponding to each loan request. Loan observations where the expected probability of default was 7.61 were not included in this model because the lenders in both Kansas and Indiana denied all of these loan requests. The two-limit Tobit model is specified as follows:

$$(4)\quad L_i = \beta_0 + \beta_1 CHAR_i + \beta_2 FICO_i + \beta_3 EXCFRK_i + \beta_4 AVGFRK_i + \beta_5 PSUPQ_i + \beta_6 PSMID_i + \beta_7 CR3_i + \beta_8 CR4_i + \beta_9 ASSETSIZ_i + \beta_{10} ROA_i + \beta_{11} NCLTL_i + \beta_{12} EXP_i + \beta_{13} PTIME_i + \varepsilon_\beta .$$

In the second two-limit Tobit model estimated, the variable *CR* represents the credit risk or expected probability of default corresponding to each loan request. Contrary to the first two-limit Tobit model, the analysis includes all observations where sufficient information was provided. The second two-limit Tobit model is specified as follows:

$$(5)\quad L_i = \beta_0 + \beta_1 CHAR_i + \beta_2 FICO_i + \beta_3 EXCFRK_i + \beta_4 AVGFRK_i + \beta_5 PSUPQ_i + \beta_6 PSMID_i + \beta_7 CR_i + \beta_8 ASSETSIZ_i + \beta_9 ROA_i + \beta_{10} NCLTL_i + \beta_{11} EXP_i + \beta_{12} PTIME_i + \varepsilon_\beta .$$

Both models in equations (4) and (5) are estimated using the PROC QLIM procedure in SAS to identify the characteristics important in determining loan approval.

Interest Rate

The interest rate offered on only the approved loan observations is included as the dependent variable in two separate ordinary least squares regression models (denied loans are excluded in this analysis). The first model, which includes the same independent variables as the first two-limit Tobit model, is specified as follows:

$$(6)\quad R_i = \alpha_0 + \alpha_1 CHAR_i + \alpha_2 FICO_i + \alpha_3 EXCFRK_i + \alpha_4 AVGFRK_i + \alpha_5 PSUPQ_i + \alpha_6 PSMID_i + \alpha_7 CR3_i + \alpha_8 CR4_i + \alpha_9 ASSETSIZ_i + \alpha_{10} ROA_i + \alpha_{11} NCLTL_i + \alpha_{12} EXP_i + \alpha_{13} PTIME_i + \varepsilon_\alpha .$$

The second model includes the same independent variables used in the second two-limit Tobit model and is specified as follows:

$$(7)\quad R_i = \alpha_0 + \alpha_1 CHAR_i + \alpha_2 FICO_i + \alpha_3 EXCFRK_i + \alpha_4 AVGFRK_i + \alpha_5 PSUPQ_i + \alpha_6 PSMID_i + \alpha_7 CR_i + \alpha_8 ASSETSIZ_i + \alpha_9 ROA_i + \alpha_{10} NCLTL_i + \alpha_{11} EXP_i + \alpha_{12} PTIME_i + \varepsilon_\alpha .$$

Results

Overall Survey Response

One hundred eighteen usable responses were returned, resulting in a total response rate of 38.82% for the lending offices in Kansas (Table 3). A breakdown indicates that 106 responses were received from commercial banks, and 12 responses from the Farm Credit System. One hundred seventeen of the participating lenders provided responses to the four loan requests they were assigned, while one lender only responded to three of the given loan requests, resulting in 471 loan observations for Kansas.

In Indiana, 52 usable responses were returned from commercial banks and nine were received from the Farm Credit System, resulting in 244 observations from Indiana. The final survey response rate was 48.41% for the lenders in Indiana. The combined total response rate for both Kansas and Indiana was 41.91% for commercial banks and 38.18% for Farm Credit Services, giving a total lender response rate of 41.44% (Table 3).

Table 3. Summary of Response Rates by Financial Institutions

Lending Offices	Kansas	Indiana	Total
Commercial Banks	38.27%	52.00%	41.91%
Farm Credit Services	44.44%	32.14%	38.18%
Total	38.82%	48.41%	41.44%

Note: The calculations for the response rates are derived using the number of banks instead of the number of lending offices.

Table 4. Distribution of Responses to Hypothetical Agricultural Loan Requests

	Kansas		Indiana	
Factors and Levels	**Frequency**	**Percent**	**Frequency**	**Percent**
Character:				
Positive	238	50.53	130	53.28
Negative	233	49.47	114	46.72
FICO Score:				
725	232	49.26	129	52.87
560	239	50.74	115	47.13
Financial Record Keeping:				
Excellent	155	32.91	80	32.79
Average	168	35.67	83	34.02
Poor	148	31.42	81	33.20
Productive Standing:				
Upper Quartile	178	37.79	92	37.70
Middle	140	29.72	75	30.74
Lower Quartile	153	32.48	77	31.56
Credit Risk Levels:				
1	131	27.81	53	21.72
2	129	27.39	60	24.59
3	110	23.35	66	27.05
4	101	21.44	65	26.64

Notes: The factors and levels correspond to those discussed in the experimental design section. The cumulative percentage for some factors and levels does not equal 100% due to rounding error.

Survey Results

This segment is divided into three sections which correspond to specific components of the survey instrument: (*a*) loan requests, (*b*) bank characteristics, and (*c*) loan officer characteristics.

Loan Requests

Since the results are dependent upon the specific loan requests to which lenders responded, it is important to examine the responses received to assess nonresponse bias. A summary of the distribution of responses obtained from Kansas and Indiana lenders on the combinations of hypothetical agricultural loan requests is presented in Table 4. The distribution of responses received should correspond to scenarios representing an expected percentage for all levels of that factor. The expected percentage for character and Fair Isaac credit bureau score is 50%, while the expected percentage for financial record keeping and productive standing is 33.33%. Credit risk is defined by four levels; therefore, the expected percentage for each level is 25%. A subjective analysis of the distribution shows that the responses received are consistent with the expected percentages for all factors and their levels.

Table 5 summarizes the distribution of decisions made by the lenders regarding loan approval or denial. Although lenders in both states approved more loans than they denied, lenders in Indiana approved 59.58% of the loans in comparison to 57.75% by lenders in Kansas. As reported in Table 6, the average loan amount offered by Kansas lenders on both approved and denied loans was $44,994, while the corresponding average loan amount offered by Indiana lenders was $43,491.

Table 5. Distribution of Decisions by Lenders Regarding Loan Approval or Denial

	Kansas		Indiana	
Decision	**Frequency**	**Percent**	**Frequency**	**Percent**
Approve Loan	272	57.75	143	59.58
Deny Loan	199	42.25	97	40.42

Table 6. Summary Statistics of Loan Amount, Interest Rate, and Terms

Description	Mean	Standard Deviation	Minimum	Maximum	No. of Observations
Kansas:					
Loan Amount, A & D	$44,994	$52,863	$0	$115,000	471
Loan Amount, A	$106,458	$7,163	$68,000	$115,000	197
Interest Rate	7.55%	0.77%	5.75%	9.75%	197
Years	6.27	0.92	4.50	7.00	197
Indiana:					
Loan Amount, A & D	$43,491	$53,160	$0	$110,000	240
Loan Amount, A	$107,449	$8,257	$50,000	$110,000	91
Interest Rate	7.17%	0.72%	5.60%	8.75%	91
Years	6.15	1.06	3.00	7.00	91

Notes: Loan Amount, A & D = the loan amount on both approved and denied loan requests; Loan Amount, A = the loan amount on loan requests that were approved.

However, the average loan amount offered by Indiana lenders on approved loans was $107,449 compared to $106,458 offered by Kansas lenders. The average interest rate offered by Indiana lenders was 38 basis points lower, and ranged from 5.60% to 8.75%; the standard deviation was 0.72%. The average interest rate offered by Kansas lenders was 7.55%, ranging from 5.75% to 9.75%; the standard deviation was 0.77%. On average, lenders in Kansas were willing to extend the loan for 6.27 years while lenders in Indiana were willing to loan for only 6.15 years. Some lenders in both states commented that they traditionally approve machinery and equipment loans for five years, but were willing to approve the loan for six years since the borrower was requesting a seven-year loan.

The interest rate offered by lenders in Kansas was on average only nine basis points higher than their typical interest rate, and ranged from 125 basis points lower to 200 basis points higher (Table 7). Indiana lenders offered an interest rate that was on average 15 basis points higher than their typical interest rate, with a range from -100 basis points to +200 basis points. Numerous lenders in both Kansas and Indiana commented that the interest rate was a specific percentage above the Wall Street Prime or their bank prime rate.

Bank Characteristics

Total assets (*ASSETSIZ*) for the 113 responding banks in Kansas averaged $5.46 billion and ranged from $200,000 to $195 billion, with a standard deviation of $28.46 billion (Table 8). A breakdown indicates 47.35% of these banks had total assets less than $100 million. The average total assets for the 53 responding banks in Indiana were $46.85 billion, and ranged from $890,000 to $1,157.25 billion; the standard deviation was $179.28 billion. A breakdown shows 14.75% of these banks had total assets of $100 million or less.

Table 7. Summary Statistics of Comparisons of Differences in Typical Interest Rates

Description	Mean	Standard Deviation	Minimum	Maximum	No. of Observations
Kansas:					
Typical Interest Rate	0.0887%	0.4397%	-1.25%	2.00%	197
Indiana:					
Typical Interest Rate	0.1475%	0.4509%	-1.00%	2.00%	89

Notes: The data presented in this table correspond to the differences between the interest rates offered by the lenders and their typical interest rates (i.e., how much higher or lower is this rate).

Table 8. Summary Statistics of Responding Banks

Bank Characteristic	Mean	Standard Deviation	Minimum	Maximum	No. of Banks
Kansas:					
Total Assets (*ASSETSIZ*)	$5.46 bil.	$28.46 bil.	$0.0002 bil.	$195.00 bil.	113
Capital Asset Ratio (*CA*)	13.37%	10.97%	1.06%	100.00%	108
Agricultural Loan Ratio (*ALTL*)	46.62%	29.37%	1.60%	100.00%	110
Return on Assets (*ROA*)	1.51%	1.01%	-0.77%	7.14%	105
Loan-Deposit Ratio (*LNDE*)	71.78%	18.21%	31.00%	113.00%	100
Noncurrent Loans to Total Loans (*NCLTL*)	1.65%	2.76%	0.00%	25.00%	105
Indiana:					
Total Assets (*ASSETSIZ*)	$46.85 bil.	$179.28 bil.	$0.0089 bil.	$1,157.25 bil.	53
Capital Asset Ratio (*CA*)	11.95%	6.53%	1.01%	50.00%	44
Agricultural Loan Ratio (*ALTL*)	27.10%	27.49%	0.40%	88.60%	46
Return on Assets (*ROA*)	1.33%	0.53%	0.38%	2.40%	48
Loan-Deposit Ratio (*LNDE*)	84.67%	14.52%	50.00%	112.00%	40
Noncurrent Loans to Total Loans (*NCLTL*)	1.49%	1.89%	0.01%	11.16%	40

Notes: The number of banks varies across bank characteristics because (*a*) some of the responding lenders did not answer the specific question, and (*b*) the number of banks that provided their Loan Deposit Ratio only represents commercial bank lending offices. Farm Credit Services is not a depository institution; therefore, there is no loan deposit ratio.

The mean capital-to-asset ratio (*CA*) for the 108 responding banks in Kansas was 13.37%, ranging from 1.06% to 100.00% with a standard deviation of 10.97%. Results show 12.53% of these banks had a ratio of 7.00% or less, 35.67% had a ratio between 7.00% and 10.00%, and 51.80% had a ratio greater than 10.00%. The mean ratio for the 44 responding banks in Indiana was 11.95%, and ranged from 1.01% to 50.00%; the standard deviation was 6.53%. Results indicate 21.31% of these banks had a ratio of 7.00% or less, 27.87% had a ratio between 7.00% and 10.00%, and 50.82% had a ratio greater than 10.00%.

The average agricultural loan ratio (*ALTL*) for the 110 responding banks in Kansas was 46.62%, ranging from 1.60% to 100.00% with a standard deviation of 29.37% A breakdown reveals 33.76% of these banks had a ratio of 25.00% or less, 41.61% had a ratio between 25.00% and 65.00%, and 24.63% had a ratio greater than 65.00%. The mean ratio for the 46 responding banks in Indiana was 27.10%, and ranged from 0.40% to 88.60%; the standard deviation was 27.49%. A breakdown indicates 68.85% of the banks had a ratio of 25.00% or less, 16.39% had a ratio between 25.00% and 65.00%, and 14.75% had a ratio greater than 65.00%.

Table 9. Summary Statistics for Responding Lenders

Loan Officer Characteristic	Mean	Standard Deviation	Minimum	Maximum	No. of Lenders
Kansas:					
EXP (years)	16.03	9.10	0.67	40.00	116
PTIME	59.30%	28.56%	2.00%	100.00%	116
MLA	$324,912	$426,761	$0	$2,000,000	113
Indiana:					
EXP (years)	17.54	9.54	1.00	37.00	59
PTIME	60.36%	32.75%	5.00%	100.00%	59
MLA	$662,222	$2,213,955	$0	$15,000,000	54

Notes: The number of lenders varies across loan officer characteristics because some of the responding lenders did not answer the specific question. *EXP* = agricultural lending experience, *PTIME* = time spent on agricultural lending, and *MLA* = maximum lending authority.

The mean return on assets (*ROA*) for the 105 responding banks in Kansas was 1.51%, ranging from -0.77% to 7.14% with a standard deviation of 1.01%. Results show 35.46% of these banks had an *ROA* of less than 1.00%. The mean *ROA* for the 48 responding banks in Indiana was 1.33%, and ranged from 0.38% to 2.40%; the standard deviation was 0.53%. Results show 39.34% of these banks had an *ROA* of 1.00% or less.

The average loan-to-deposit ratio (*LNDE*) for the 100 responding banks in Kansas was 71.78%, ranging from 31.00% to 113.00% with a standard deviation of 18.21%. A breakdown indicates 46.50% of the banks had a ratio of 65% or less, 28.03% had a ratio between 65% and 80%, and 25.48% had a ratio greater than 80%. For the 40 responding banks in Indiana, the average loan-to-deposit ratio was 84.67%, ranging from 50.00% to 112.00% with a standard deviation of 14.52%. A breakdown indicates 39.34% of the banks had a ratio of 65% or less, 16.39% had a ratio between 65% and 80%, and 44.26% had a ratio greater than 80%.

Finally, the average noncurrent loans to total loans (*NCLTL*) for the 105 responding banks in Kansas was 1.65%, and ranged from 0.00% to 25.00%; the standard deviation was 2.76%. Results show 61.78% of these banks had a ratio of 1.00% or less, 32.27% had a ratio between 1.00% and 4.00%, and 5.94% had a ratio greater than 4.00%. The mean ratio for the 40 responding banks in Indiana was 1.49%, ranging from 0.01% to 11.16% with a standard deviation of 1.89%. Results show 65.57% of these banks had a ratio of 1.00% or less, 29.51% had a ratio between 1.00% and 4.00%, and 4.92% had a ratio greater than 4.00%.

Loan Officer Characteristics

Table 9 reports summary statistics for loan officer characteristics. The average number of years of experience as an agricultural loan officer (*EXP*) for the 116 responding lenders in Kansas was 16.03 years, ranging from 8 months to 40 years; the standard deviation was 9.10 years. The mean EXP for the 59 responding lenders in Indiana was 17.54 years, and ranged from 1 year to 37 years with a standard deviation of 9.54 years.

The mean percentage of time Kansas lenders spend on agricultural loans (*PTIME*) was 59.30%, ranging from 2% to 100%. A breakdown indicates 19.32% of these lenders spend 25% or less of their time on agricultural loans, 28.03% spend between 25% and 50%, 22.08% spend between 50% and 75%, and 30.57% spend greater than 75% of their time on agricultural loans. For the Indiana

Table 10. Regression Results from Tobit Model 1 for the Proportion of Loan Granted

	Kansas		Indiana		All	
Variable	**Coefficient**	***p*-Value**	**Coefficient**	***p*-Value**	**Coefficient**	***p*-Value**
Intercept	-1.7064***	0.0012	-3.5242*	0.0565	-2.1659***	< 0.0001
CHAR	0.8130***	0.0003	0.7808	0.2653	0.7685***	0.0007
FICO	0.9814***	< 0.0001	3.3167***	0.0019	1.4261***	< 0.0001
EXCFRK	0.4078	0.1220	1.6065*	0.0781	0.7042**	0.0107
AVGFRK	0.0608	0.8135	0.9776	0.2312	0.3129	0.2351
PSUPQ	0.4376*	0.0885	-1.0768	0.2092	0.2107	0.4159
PSMID	0.4934*	0.0693	-1.1229	0.2056	0.2201	0.4202
CR3	1.3193***	< 0.0001	3.0858***	0.0009	1.6344***	< 0.0001
CR4	3.7685***	< 0.0001	7.8061***	0.0004	4.5208***	< 0.0001
ASSETSIZ	-0.0034	0.4582	-0.0023	0.4249	-0.0013	0.3740
ROA	-0.2328**	0.0419	-0.6505	0.3912	-0.2919**	0.0291
NCLTL	-0.0896**	0.0129	-0.3757	0.1191	-0.1106***	0.0071
EXP	-1.7064***	0.0012	-3.5242*	0.0565	-2.1659***	< 0.0001
PTIME	0.8130***	0.0003	0.7808	0.2653	0.7685***	0.0007
Σ	0.9814***	< 0.0001	3.3167***	0.0019	1.4261***	< 0.0001
$\mathcal{L}$, Mean	0.5523		0.5304		0.5452	
$\mathcal{L}$, Standard Error	0.4842		0.4939		0.4869	
Obs. Lower Bound	129		67		196	
Obs. Upper Bound	115		65		180	
Total Observations	229		145		444	
Log Likelihood	-233.52		-93.82		-339.51	

Note: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

lenders, the mean *PTIME* was 60.36%, and ranged from 5% to 100%. A breakdown indicates 27.87% of these lenders spend 25% or less of their time on agricultural loans, 19.67% spend between 25% and 50%, 11.48% spend between 50% and 75%, and 40.98% spend greater than 75% of their time on agricultural loans.

The average maximum lending authority (*MLA*) for the Kansas lenders was $324,912, and ranged from $0 to $2,000,000. Results show that 71.13% had an *MLA* of $250,000 or less, 11.89% had an *MLA* between $250,000 and $500,000, and 16.99% had an *MLA* greater than $500,000. For the Indiana lenders, the mean *MLA* was $662,222, ranging from $0 to $15,000,000. Results show that 68.85% had an *MLA* of $250,000 or less, 19.67% had an *MLA* between $250,000 and $500,000, and 11.48% had an *MLA* greater than $500,000. A closer look shows that 51.59% of the 113 lenders in Kansas responding to this question had a maximum lending authority less than the requested loan amount of $110,000, while 39.34% of the 54 lenders in Indiana reported an *MLA* less than $110,000.

Loan Amount Regression Analysis

The regression results from the first two-limit Tobit model [equation (4)] in Table 10 correspond to the Kansas, Indiana, and All (total) observations, respectively. The two nonfinancial variables, which were statistically significant at the 1% level in Kansas and All, are character (*CHAR*) and Fair Isaac credit bureau score (*FICO*). *FICO* was statistically significant at the 1% level in Indiana, but *CHAR* was not statistically significant. Although both variables had a positive impact on the

Table 11. Regression Results from Tobit Model 2 for the Proportion of Loan Granted

	Kansas		Indiana		All	
Variable	**Coefficient**	***p*-Value**	**Coefficient**	***p*-Value**	**Coefficient**	***p*-Value**
Intercept	1.75383***	0.0001	3.817192**	0.0262	2.007441***	< 0.0001
CHAR	0.81574***	0.0003	0.781842	0.2631	0.766789***	0.0008
FICO	0.96760***	< 0.0001	3.332429***	0.0019	1.419319***	< 0.0001
EXCFRK	0.40883	0.1208	1.613375*	0.0764	0.705109**	0.0105
AVGFRK	0.05196	0.8399	0.952115	0.2399	0.310854	0.2378
PSUPQ	0.43811*	0.0880	-1.040909	0.2184	0.206732	0.4236
PSMID	0.49246*	0.0696	-1.146710	0.1954	0.223183	0.4129
CR	-0.94457***	< 0.0001	-1.999740***	0.0003	-1.140764***	< 0.0001
ASSETSIZ	-0.00366	0.4219	-0.002395	0.4184	-0.001308	0.3766
ROA	-0.23133**	0.0429	-0.613854	0.4121	-0.292455**	0.0286
NCLTL	-0.09005**	0.0124	-0.373152	0.1178	-0.110866***	0.0069
EXP	-0.01159	0.3033	0.030864	0.3981	-0.004862	0.6693
PTIME	1.75383***	0.0001	3.817192**	0.0262	2.007441***	< 0.0001
Σ	0.81574***	0.0003	0.781842	0.2631	0.766789***	0.0008
$\mathcal{L}$, Mean	0.4008		0.4179		0.4061	
$\mathcal{L}$, Standard Error	0.4805		0.4890		0.4828	
Obs. Lower Bound	242		106		348	
Obs. Upper Bound	115		65		180	
Total Observations	412		184		596	
Log Likelihood	-233.84		-93.91		-339.76	

Note: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

proportion granted in Kansas, Indiana, and All, results suggest that *FICO* has a larger impact on the proportion granted.

The variables corresponding to the borrower's financial record keeping abilities (*EXCFRK* and *AVGFRK*) suggest that as the borrower's abilities increased, the proportion of the loan approved increased, which is as expected. However, *EXCFRK* is the only variable that was statistically significant at the 10% level in Indiana and at the 5% level in All. The two productive standing variables (*PSUPQ* and *PSMID*) were both statistically significant at the 10% level in Kansas, but were not statistically significant in Indiana and All. The coefficients for *PSMID* are larger than the coefficients for *PSUPQ*, which may imply either that productive standing is not an important factor in the agricultural loan decision-making process or that it is especially important to avoid borrowers in the lower quartile.

The two financial variables (*CR*3 and *CR*4), were both statistically significant at the 1% level in Kansas, Indiana, and All. The findings show that as the expected probability of default for a loan request decreased, the proportion of the loan approved increased, which is as anticipated. The results also suggest that lenders may have been willing to approve a larger amount on corresponding scenarios because of the financial condition of the farm since the coefficients for these variables were greater than one. This finding may be an indication of unused credit capacity for these financial conditions.

Regression results for the bank characteristics (*ASSETSIZ*, *ROA*, and *NCLTL*) all suggest they had a negative

Table 12. Regression Results from Interest Rate Model 1 for Approved Loan Observations

	Kansas		Indiana		All	
Variable	**Coefficient**	***p*-Value**	**Coefficient**	***p*-Value**	**Coefficient**	***p*-Value**
Intercept	8.5151***	< 0.0001	8.2775***	< 0.0001	8.5253***	< 0.0001
CHAR	-0.1073	0.3530	-0.1652	0.3216	-0.1781*	0.0639
FICO	-0.2459**	0.0327	-0.3655*	0.0524	-0.2975***	0.0024
EXCFRK	-0.1294	0.3467	-0.3558	0.1296	-0.2512**	0.0319
AVGFRK	-0.1857	0.1675	-0.2255	0.3310	-0.2604**	0.0247
PSUPQ	-0.1730	0.1978	0.1123	0.5948	-0.0776	0.4908
PSMID	0.0194	0.8910	0.3276	0.1241	0.1127	0.3418
CR3	-0.1426	0.2191	-0.2092	0.2770	-0.1451	0.1390
CR4	-0.8561***	0.0002	-1.0096***	0.0095	-0.9294***	< 0.0001
ASSETSIZ	-0.0051**	0.0343	0.0003	0.6132	-0.0004	0.4599
ROA	-0.1778**	0.0203	-0.0878	0.6628	-0.1624**	0.0216
NCLTL	0.0281	0.1434	0.2405***	0.0029	0.0504***	0.0071
EXP	-0.0143**	0.0191	-0.0146	0.1457	-0.0119**	0.0202
PTIME	0.0046***	0.0300	-0.0019	0.4955	0.0027	0.1105
R^2	0.2448		0.4026		0.2286	
Adjusted R^2	0.1811		0.2687		0.1843	
F-Statistic	3.84		3.01		5.15	
RMSE	0.6986		0.6577		0.7104	
Total Observations	168		72		240	

Note: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

impact on the proportion of loan granted. However, *ASSETSIZ* was not statistically significant in Kansas, Indiana, and All, while *ROA* and *NCLTL* were statistically significant in Kansas and All. The results imply that years of agricultural loan officer experience (*EXP*) negatively affected the proportion granted in Kansas, Indiana, and All. The amount of time spent on agricultural loans (*PTIME*) had a positive impact on the proportion granted in Kansas, Indiana, and All. The relationships for both of these loan officer characteristics were statistically significant at the 1% level in Kansas and All, while *EXP* was the only statistically significant loan officer characteristic in Indiana.

The regression results from the second two-limit Tobit model [equation (5)] reported in Table 11 correspond to the Kansas, Indiana, and All observations, respectively. The variable *CR* represents the credit risk or expected probability of default that corresponds to each loan request. The results presented in this table are consistent with those shown in Table 10. After redefining the credit risk variable, results continue to confirm that as the expected probability of default for a loan request increased, the proportion of the loan granted decreased.

Interest Rate Regression Analysis

The regression results for the first interest rate model [equation (6)] in Table 12 correspond to the Kansas, Indiana, and All observations, respectively. Both *CHAR* and *FICO* were found to be inversely related to the interest rate charged by the financial institution. However, with the exception of *CHAR* in All, *FICO* is the only one of these two nonfinancial variables that was statistically significant—i.e., at the 5% level in Kansas, 10% level in Indiana, and the 1% level in All.

Table 13. Regression Results from Interest Rate Model 2 for Approved Loan Observations

	Kansas		Indiana		All	
Variable	**Coefficient**	***p*-Value**	**Coefficient**	***p*-Value**	**Coefficient**	***p*-Value**
Intercept	7.8054***	< 0.0001	7.4034***	< 0.0001	7.7655***	< 0.0001
CHAR	-0.1285	0.2710	-0.1900	0.2566	-0.1998**	0.0410
FICO	-0.2185*	0.0593	-0.3494*	0.0651	-0.2678***	0.0069
EXCFRK	-0.1390	0.3184	-0.3658	0.1224	-0.2628**	0.0276
AVGFRK	-0.1608	0.2363	-0.2423	0.3004	-0.2514**	0.0332
PSUPQ	-0.1693	0.2135	0.1522	0.4715	-0.0646	0.5732
PSMID	0.0178	0.9014	0.3162	0.1406	0.1020	0.3982
CR	0.2185***	0.0002	0.2659***	0.0070	0.2380***	< 0.0001
ASSETSIZ	-0.0044*	0.0639	0.0002	0.7135	-0.0005	0.3907
ROA	-0.1922**	0.0131	-0.1095	0.5892	-0.1772**	0.0138
NCLTL	0.0287	0.1394	0.2595***	0.0013	0.0534***	0.0051
EXP	-0.0160***	0.0093	-0.0131	0.1917	-0.0122**	0.0197
PTIME	0.0054**	0.0105	-0.0019	0.5001	0.0031*	0.0701
R^2	0.2194		0.3812		0.1954	
Adjusted R^2	0.1589		0.2553		0.1528	
F-Statistic	3.63		3.03		4.59	
RMSE	0.7080		0.6637		0.7240	
Total Observations	168		72		240	

Note: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The borrower's financial record keeping abilities (*EXCFRK* and *AVGFRK*) display consistent signs but were not statistically significant for Kansas and Indiana. Although an interpretation of these results yields little meaning, results do show that *EXCFRK* and *AVGFRK* were statistically significant at the 5% level in All. The results for the borrower's productive standing (*PSUPQ* and *PSMID*) display inconsistent results across the estimates of these variables, and results were not statistically significant.

Results show that the two financial variables (*CR*3 and *CR*4) reduced the impact on the interest rate in Kansas, Indiana, and All. This suggests that as the expected probability of default for a loan request decreased, the interest charged by the financial institution decreased as well, which is as expected. However, *CR*4 was statistically significant at the 1% level in Kansas, Indiana, and All, but *CR*3 was not statistically significant.

The bank characteristics (*ASSETSIZ*, *ROA*, and *NCLTL*) showed mixed results in the interest rate model. The results imply that *ASSETSIZ* had an inverse relationship with the interest rate in Kansas and All, but had a direct impact on the interest rate in Indiana. *ASSETSIZ* was statistically significant only at the 5% level in Kansas. The regression results for *ROA* suggest that it had an inverse relationship with the interest rate charged by lenders in Kansas, Indiana, and All; however, *ROA* was only statistically significant at the 5% level in Kansas and All. Increases in *NCLTL* increased the interest rate in Kansas, Indiana, and All. Nonetheless, *NCLTL* was only statistically significant at the 1% level in Indiana and All.

The loan officer characteristics (*EXP* and *PTIME*) also showed mixed results in the interest rate model. An increase in *EXP* decreased the interest rate in Kansas, Indiana, and All, but was only statistically significant at the 5% level in Kansas and

All. The results also suggest that an increase in *PTIME* increased the interest rate charged by the lenders in Kansas and All, but decreased the interest rate in Indiana. *PTIME* was statistically significant only at the 1% level in Kansas.

The regression results from the second model [equation (7)] reported in Table 13 correspond to the Kansas, Indiana, and All observations, respectively. The total number of observations used in the first and second OLS models is the same because the lenders in both Kansas and Indiana denied all loan requests where the expected probability of default was 7.61.

Conclusions

The primary objective of this study was to analyze the factors considered by financial institutions when lending to farm borrowers. To obtain the required data, a survey of financial institutions in both Kansas and Indiana was conducted where agricultural lenders responded to four hypothetical agricultural loan requests. Each loan request differed by the borrower's character, financial record keeping, productive standing, Fair Isaac credit bureau score, and credit risk. Lenders also provided information about themselves and their financial institution.

Two-limit Tobit models identified the borrower and lender characteristics important in determining loan approval. The results suggest that the two nonfinancial variables—character and Fair Isaac credit bureau score—both significantly influenced the proportion granted in Kansas, while the Fair Isaac credit bureau score significantly influenced the proportion granted in Indiana. The financial variables representing credit risk, or the expected probability of default, significantly influenced the proportion granted by financial institutions. Return on assets and noncurrent loans to total loans were the only bank characteristics that significantly influenced the proportion granted in Kansas. The loan officer characteristics—percentage of time lenders spent on agricultural loans, and number of years of experience as an agricultural loan officer—significantly influenced the proportion granted in Kansas.

Interest rate models identified the borrower and lender characteristics important in determining interest rates. Findings reveal that the Fair Isaac credit bureau score had an inverse relationship with and significantly influenced the interest rate charged by financial institutions. The credit risk variables had an inverse relationship with the interest rate charged by financial institutions.

The bank characteristics suggest that total assets and return on assets had an inverse relationship with the interest rate in Kansas, and were both statistically significant at the 5% level. The ratio of noncurrent loans to total loans had a positive correlation with and statistically influenced the interest rate in Indiana. The results imply that the lender experience as an agricultural loan officer inversely affected the interest rate and was statistically significant at the 5% level in Kansas. Further, time spent on agricultural lending had a positive correlation with the interest rate charged by the lenders in Kansas and was statistically significant at the 1% level.

Financial condition and character are both important in the loan evaluation process, consistent with the findings of Gustafson, Beyer, and Saxowksy (1991). Not only are these factors important in the discussion to extend credit, but they are also important in determining the price charged for that credit, consistent with the findings of Ellinger, Splett, and Barry (1992). Credit bureau information plays an important role in the loan approval and pricing decisions.

Differences in interest rates based upon credit evaluation are more pronounced in this analysis compared to findings reported by Pflueger and Barry (1986). Consistent with the findings of Dixon, Ahrendsen, and Barry (1993), less profitable banks tend to charge higher

interest rates. The results of this analysis confirm much of the conventional wisdom found in the previous agricultural finance literature; however, it seems that interest rate differences based on credit quality are wider than in the past.

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FSA Direct Loan Targeting: Successful and Financially Necessary?

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Abstract

The Farm Service Agency (FSA) direct farm loan program provides credit to family-sized farms including those operated by beginning farmers and socially disadvantaged applicants. Approximately 37% of all U.S. farms are estimated to be eligible for FSA direct loans when farm size, credit needs, farming experience, and occupation are taken into account. However, market penetration rates for various borrower cohorts range from 0.8% to 4.6% for FY 2000–2003. In general, beginning farmers have weaker financial characteristics than non-beginning farmers. Yet, the same result is not found when comparing socially disadvantaged farmers with non-socially disadvantaged farmers, such that there are few significant differences or the differences in financial characteristics are mixed. Overall, results indicate FSA direct farm loan borrowers have weaker financial characteristics than eligible, non-FSA direct farm loan borrowers, implying FSA is serving farmers likely to be denied credit by commercial lenders.

Key words: beginning farmer, Farm Service Agency, federal direct loan, socially disadvantaged

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Farm Service Agency (FSA) farm loan programs are designed to provide credit to family-sized farms unable to obtain credit from conventional sources at reasonable rates and terms despite having sufficient cash flow to repay and an ability to fully securitize the loan. FSA loans are divided into loans made directly to farmers (direct) and loans made to farmers by other lenders with an FSA guarantee (guaranteed). This study focuses on direct loans.

FSA's direct farm loan program provides short- to intermediate-term farm operating loans (OL) and long-term farm ownership (FO) loans as well as emergency (EM) loans to family-sized farms. Federal legislation mandates that portions of FO and OL loan funds be targeted to family-sized farm subgroups of socially disadvantaged (SDA) and beginning farmer (BF) applicants.

FSA recognizes an SDA farmer or rancher as "one of a group whose members have been subjected to racial, ethnic, or gender prejudice because of his or her identity as a member of the group without regard to his or her individual qualities. SDA groups are women, African Americans, American Indians, Alaskan Natives, Hispanics, Asian Americans, and Pacific Islanders" (USDA/FSA, 2006). For OL purposes, a BF is a farmer who meets the general OL eligibility criteria and has 10 or less years of farming experience. For FO purposes, a BF is a farmer who meets the general FO criteria, has 3–10 years of farming experience, and owns acreage which does not exceed 30% of the county average farm size.[1]

[1] Prior to 2004, the acreage limit was 25% of the county average farm size (U.S. 7 CFR 1943.4).

Previously, Dodson and Koenig (2003) examined reasons for varying levels of FSA market penetration in the overall direct loan market. Their study found the use of FSA loan programs was greater in counties with lower per capita income, counties with FSA loan service centers, states with greater FSA funding in previous years, and regions experiencing greater farm financial stress. Use of direct loan programs was found to be higher in counties with no private-sector agricultural lender offices in the county or within 10 miles of the county boundaries.

While FSA's direct farm loan program has multiple goals and services, this analysis focuses on whether the agency is successfully serving family farms—particularly small family, BF, and SDA farms. The analysis also assesses whether farm loan program targeting is necessary based on financial characteristic differences among family farm groups. To address these questions, the remaining sections of the article are organized as follows: (*a*) a description of loan market segments served,
(*b*) an analysis of market penetration among different market segments, (*c*) a comparison of borrower financial characteristics among different cohorts, and (*d*) a summary of study findings and presentation of concluding remarks.

FSA Direct Loans to Targeted Clientele

Recent FSA direct loan data from fiscal years (FY) 2000–2003 are used to focus the analysis on current loan activities. The FSA New Loan (NL) data set[2] shows the agency made 60,151 direct loans to 45,016 borrowers during the period (Table 1). OL loans accounted for 79% of the loans, while FO and EM loans accounted for 10% and 11%, respectively.

Table 1 reports a total of 47,540 OL loans were originated with $2,653,767,897 total principal for an average loan size of $55,822 during FY 2000–2003. The $390,188,835 used for the 6,484 EM loans originated over the same four years resulted in a $60,177 average loan size. For the 6,127 FO loans, the average loan size was $113,739, about double the OL and EM average loan sizes.

As found by Nwoha et al. (2005) for FY 2000–2003 and by Dodson and Koenig (2003) for FY 1995–1999, FSA loans are geographically dispersed. The location of OL and FO loans partly reflects the regional dispersion of eligible borrowers, while the location of EM loans is driven by the occurrence of weather-related natural disasters.

Small Family Farm Borrowers

A "small" family farm is defined here as having annual sales less than $250,000 per year as suggested by the National Commission on Small Farms (USDA/ERS, 2001).[3] One indication of FSA loan activity among small farms is the percentage of FSA loans made to small farms based on USDA's Agricultural Resource Management Survey (ARMS) data for 2000–2003.[4] Nationwide, ARMS data indicate 78% of farms originating FSA

[2] FSA's internal Farm Loan Program Making and Loan Servicing database provides detailed information about every loan originated. The database contains information about the borrower (tax identification or social security number, county and state of residence, race, ethnicity, and gender) and loan (number, type, assistance type, amount, and origination date). The database contains information on 70,923 loans made to 54,984 borrowers during FY 2000–2003. Of these loans, 9,747 were youth loans made to 9,062 youth borrowers. Since the focus of this article is not on youth programs, youth loans were excluded from the analysis presented here. An additional 1,025 loans were removed from the database based on their unusual assistance types resulting in the New Loan (NL) data set used in this study.

[3] FSA does not use a strict small farm definition to direct its lending efforts.

[4] The ARMS is conducted annually by the USDA, which collects detailed information on farming practices and farm financial conditions including credit sources. The ARMS samples only a small proportion of the overall U.S. farm population. However, the sample database includes a set of complex replicate weights (expansion factors) designed to expand the sample whereby overall farm population estimates can be obtained. These expanded estimates are reported here.

Table 1. FSA Loan Number, Average Loan Amount, and Borrower Number by Loan Assistance Type, FY 2000–2003

Assistance Type[a]		No. of Loans	Average Loan ($)	No. of Borrowers[b]
All:	OL	47,540	55,822	37,729
	FO	6,127	113,739	6,067
	EM	6,484	60,177	6,018
	Total	60,151	62,191	45,016
SDA:[c]	OL	6,512	46,692	5,076
	FO	1,098	116,110	1,083
	Total	7,610	56,708	5,724
BF:[c]	OL	19,804	52,055	14,824
	FO	4,144	114,709	4,111
	Total	23,948	62,897	17,733

Source: Computed from FSA New Loan data set.

[a] OL = operating loans, FO = farm ownership loans, EM = emergency loans, SDA = socially disadvantaged, and BF = beginning farmer.

[b] While there are 28,852 unique borrowers within the four-year period, borrowers are counted as new borrowers for each year they obtain a new loan. Therefore, a unique borrower can appear as frequently as four times in the number of new borrowers, which results in a total of 45,016 new borrowers. A borrower who obtains multiple loans within a year is counted once for each loan type (OL, FO, and EM) obtained within the year. Therefore, the sum of the number of new borrowers across loan types exceeds the total number of borrowers for each assistance type (All, SDA, or BF).

[c] EM loans do not have SDA or BF assistance types.

direct loans are small family farms.[5] This estimated percentage is computed as the four-year total number of small farms reporting one or more FSA-sourced loans originated during the calendar year of the survey divided by the four-year total number of all farms reporting one or more FSA-sourced loans originated during the calendar year of the survey.

Data from the FSA Farm and Home Plan (FHP) data set, which contains data from direct loan applicants, can be used to estimate farm sales.[6] This provides another measure of FSA small farm service. The FHP contains balance sheet, income, and demographic information about the applicant. Financial information from the FHP is matched with loan information from the NL data set for 19,153 borrowers, who represent 42.5% of the total number of borrowers in the NL data set.[7] The FHP's gross income variable (crop income plus livestock income plus other farm income) is used as a proxy for sales, thus allowing an estimate of small farm numbers in the NL data set. The combined NL and FHP data set is also used to develop state-level estimates of the share of farms receiving FSA loans that are small.[8]

The number of small farm borrowers as a share of total borrowers who received new FSA loans in FY 2000–2003 ranges from 74.1% for Connecticut to 100% for Alaska, Montana, and Rhode Island (Figure 1). Overall, 92.4% of the FSA borrowers operate small farms. In comparison, an estimated 88.2% of farms considered likely to be eligible for FSA loans are small farms, based on *2002 Census of Agriculture* data.[9] Thus, it appears the vast majority of FSA direct loans are being made to one of its targeted clientele groups: small family farms. The statutory lending caps of FSA's direct farm loan program probably assist FSA in assuring a majority of its funds go to small family farms, since the credit needs of small

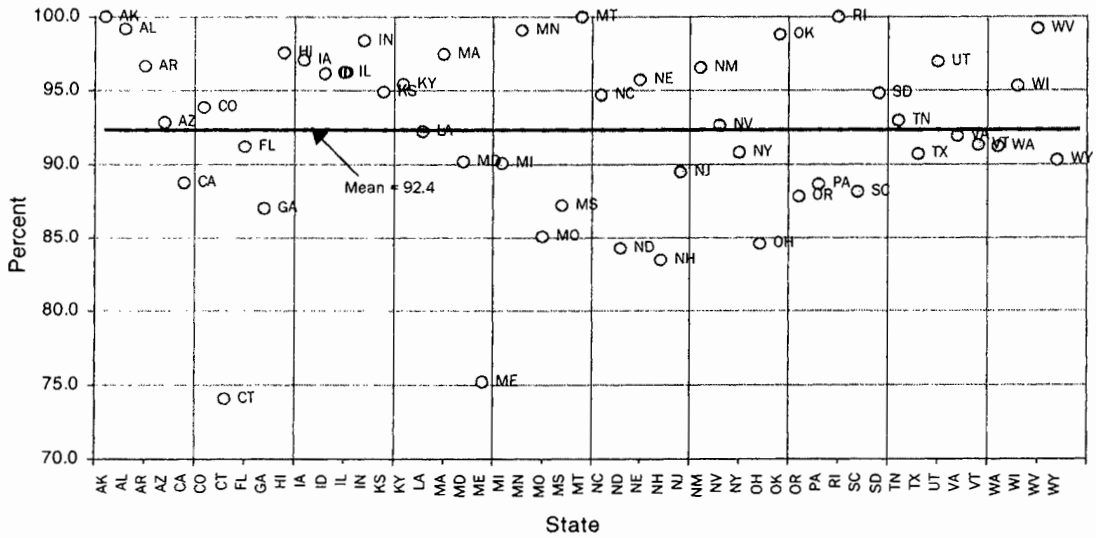
[5] Of the remaining 22% of farms originating FSA direct loans, an estimated 14% are farms with $250,000 to $499,999 in sales, 6% are farms with $500,000 to $999,999 in sales, and only 2% are farms with $1,000,000 or more in sales.

[6] The FHP was replaced by the Farm Business Plan beginning in FY 2005.

[7] Ideally, the combined NL and FHP data set would include the entire population of FSA new borrowers, but many observations in the borrower population could not be matched to a usable FHP because the FHP was not in the database or it was incomplete. The reasons for the incompleteness are not sufficiently known to the extent that the resulting sample could be represented to be random. We suspect the 19,153 observations are representative of the population. The observations are proportionate to the population in terms of loan types (FO, OL, and EM) and targeted borrowers (SDA and BF). Moreover, these data are by far the most comprehensive extant. Therefore, the following analysis is the best available for assessing borrower and farm characteristics.

[8] The ARMS data do not give reasonable estimates of FSA small farm counts by state, with nine states showing no FSA small farms at all.

[9] The definition of "eligible" farms is given shortly.



Source: Computed from combined FSA New Loan Database/Farm and Home Plan Database

Figure 1. Percent Share of Small Farm Borrowers to Total FSA Borrowers, by State (FY 2000–2003)

family farms are more likely to be met within these caps.[10]

SDA Borrowers

Under the Agricultural Credit Act of 1987 (P.L. 100-233), FSA began officially targeting SDA farmers applying for direct FO loans in FY 1989. The Food, Agriculture, Conservation, and Trade Act of 1990 (P.L. 101-624) and the Agricultural Credit Act of 1992 (P.L. 102-554) expanded SDA targeting to include OL loans and extended the SDA definition to its current form by including women. Current regulations require FSA to target a portion of its direct and guaranteed FO and OL loan funds for use exclusively by SDA farmers (7 CFR 761.208): "In the farm ownership loan program, the percentage of loan funds targeted to SDAs is based upon the state percentage of the total rural population made up of SDA groups, and the statewide percentage of total farmers who are female. In the operating loan program, the target is determined by the statewide percentage of total farmers from the SDA minority group, and the statewide percentage of total farmers who are female" (USDA/FSA, 2006). EM loans are not specifically targeted to SDA farmers.

The loan assistance type from the NL data set identifies the loan type (FO, OL, or EM) and whether or not the loan is made using targeted funds (SDA or BF).[11] During FY 2000–2003, $304,058,841 funded 6,512 SDA assistance type OL loans for a $46,692 average loan size (Table 1). The 1,098 FO loans with SDA assistance types were funded with $127,489,221 and averaged $116,110 per loan. On average, FO loans were nearly 2.5 times larger than OL loans.

Although an SDA farmer may be identified by SDA loan assistance types, an SDA (or

[10] FO and OL direct loan program indebtedness is capped at $200,000 each, and EM loan program indebtedness cannot exceed $500,000.

[11] Every loan in the NL data set has an assistance type code which indicates the funding type. For example, assistance type code 031 is "Direct Farm Ownership, Farm Enterprise, Socially Disadvantage, Ethnic" and indicates a direct FO loan was made to a farmer belonging to one or more of the SDA race/ethnicity groups.

BF) applicant could still receive a loan using nontargeted funds, perhaps due to lack of fund availability for various loan assistance types. Therefore, SDA eligible farmers are identified using data on loan assistance type, race/ethnicity, and gender from the NL data set, and should be used to measure FSA's success in serving the SDA loan market.[12]

A borrower is identified as SDA gender eligible if the indicated gender is female or if the indicated loan assistance type is SDA gender (Table 2). SDA race and ethnic borrower numbers are based on borrowers' indicated race or ethnicity. If a borrower indicated more than one race, she/he is counted once in each of the races or ethnicity. Beginning farmers are identified as those borrowers who received an FSA loan with a beginning farmer assistance type.[13]

Of the 9,172 loans identified with SDA eligible farmers (Table 2), 82% of them have SDA assistance types (i.e., are funded with targeted funds). SDA gender eligible farmers received 3,669 loans, with 77% of the loans having an SDA assistance type. Of the 5,503 loans identified as being received by SDA racial/ethnic eligible farmers, Black/African American farmers received the most (2,180 loans) of any racial/ethnic group.

Beginning Farmer Borrowers

The Agricultural Credit Act of 1992 (P.L. 102-554) initiated FSA targeting of direct loans to beginning farmers. Currently, FSA is required to target 35% of OL and 70% of FO loan funds for use by beginning farmers. Funds remain targeted for beginning farmers until September 1 of each fiscal year (USDA/FSA, 2006). In contrast, EM loans are not specifically targeted to beginning farmers.

A total of 19,804 OL BF loans were originated during FY 2000–2003 with $1,030,904,649 total principal for an average loan size of $52,055 (Table 1). By comparison, there were only 4,144 FO BF loans originated over the same four years with $475,355,940 total principal. Although there were only about one-fifth the number of FO BF loans originated relative to OL BF loans, the $114,709 average FO BF loan size was more than twice the average OL BF loan size.

BF loans are an important part of FSA direct loan activity, which is consistent with the required targeting of program funds. For the United States, 39% of the OL volume and 42% of OL loan numbers went to BF borrowers, whereas 69% of the FO volume and 68% of FO loan numbers went to BF borrowers during FY 2000–2003 (Table 1).

FSA Direct Loan Market Penetration: Is Targeting Successful?

Market penetration is used as a measure of the FSA direct farm loan program success in serving targeted clienteles. The market penetration rate is defined as the percentage of the FSA loan-eligible farm population receiving direct loans over a given time span and is computed as:

$$\textit{Market Penetration}_{Type,\,Unit} = \frac{\sum_{Year\ 2000}^{2003} \textit{No. of Unique Borrowers}_{Year,\,Type,\,Unit}}{\textit{No. of FSA Eligible Farm Operators}_{Type,\,Unit}} \cdot 100,$$

where *Type* signifies a given loan type (OL, FO, EM, or some combination of loan types);[14] *Unit* signifies the borrower

[12] Although every loan in the NL data set has an assistance type code, data on variables indicating loan recipient race/ethnicity and gender are incomplete for some loans.

[13] The NL data set does not have a farming years experience variable, which could be used to identify any beginning farmers receiving nontargeted funds. Therefore, loans to BF eligible farmers may be undercounted.

[14] For instance, an OL and FO loan type combination means that if an individual had both an OL and an FO loan within the four years, then they were only counted once in computing the combined OL and FO loan type penetration rate.

Table 2. Loan Numbers by Loan Assistance Type for Various Borrower Cohorts, FY 2000–2003

	Loan Assistance Type											
Borrower Cohort	**OL Regular**	**OL BF**	**OL BF SDA**	**OL SDA**	**FO Regular**	**FO BF**	**FO BF SDA Ethnic**	**FO BF SDA Gender**	**FO SDA Ethnic**	**FO SDA Gender**	**EM**	**Total**
SDA Gender Eligible	281	250	1,257	1,057	12	35	28	297	22	178	252	3,669
	(7.7)	(6.8)	(34.3)	(28.8)	(0.3)	(0.1)	(0.8)	(8.1)	(0.6)	(4.9)	(6.9)	(100)
American Indian	101	56	411	542	9	13	127	26	81	10	92	1,468
	(6.9)	(3.8)	(28.0)	(36.9)	(0.6)	(0.9)	(8.7)	(1.8)	(5.5)	(0.7)	(6.3)	(100)
Asian	10	4	68	160	1	0	25	4	16	4	32	324
	(3.1)	(1.2)	(21.0)	(49.4)	(0.3)	(0.0)	(7.7)	(1.2)	(4.9)	(1.2)	(9.9)	(100)
Black	25	23	803	917	1	0	49	3	72	6	281	2,180
	(1.1)	(1.1)	(36.8)	(42.1)	(0.0)	(0.0)	(2.2)	(0.1)	(3.3)	(0.3)	(12.9)	(100)
Hispanic	73	32	460	519	2	12	83	9	46	4	200	1,440
	(5.1)	(2.2)	(31.9)	(36.0)	(0.1)	(0.8)	(5.8)	(0.6)	(3.2)	(0.3)	(13.9)	(100)
Hawaiian	12	3	26	34	0	4	4	1	1	0	6	91
	(13.2)	(3.3)	(28.6)	(37.4)	(0.0)	(4.4)	(4.4)	(1.1)	(1.1)	(0.0)	(6.6)	(100)
Beginning Farmer	0	16,762	3,042	0	0	3,491	356	297	0	0	0	23,948
	(0.0)	(70.0)	(12.7)	(0.0)	(0.0)	(14.6)	(1.5)	(1.2)	(0.0)	(0.0)	(0.0)	(100)
All	24,266	16,762	3,042	3,470	1,538	3,491	356	297	267	178	6,484	60,151
	(40.3)	(27.9)	(5.1)	(5.8)	(2.6)	(5.8)	(0.6)	(0.5)	(0.4)	(0.3)	(10.8)	(100)

Source: Computed from FSA New Loan data set.

Note: The numbers in parentheses are percentage share by loan assistance type for each cohort so that the row percentages sum to 100%.

belonging to certain targeted groups in a market area (small family, BF, SDA, or all family farmers by county, state, or nation); and *Year* is the loan origination year.

The penetration analysis focuses on FSA borrowers who receive new loans, instead of any borrower having an FSA direct loan at a given point in time, to indicate recent FSA lending priorities and behavior. Therefore, the market penetration numerator is computed from the FSA NL data set and is the sum of all unique FSA direct borrowers originating a particular loan type and belonging to a certain targeted group in a given market area during FY 2000–2003. For each loan type, a borrower is only counted once during the four-year period. Thus, a borrower receiving two OL loans and one FO loan within the four years is counted as one borrower for the purposes of OL penetration, one borrower for the purposes of FO penetration, and one borrower for the purposes of combined penetration.[15]

The market penetration denominator is estimated using *2002 Census of Agriculture* data and is the sum of all FSA loan type-eligible farmers in a market area (e.g., OL, FO, EM, or some combination of loan types to small family, SDA, BF, or all family farms in a county, state, or nation) for the year 2002. Thus, the penetration rate can be viewed as the percentage of targeted, eligible farmers FSA reaches with new direct loans between 2000 and 2003.

Farms are identified as FSA eligible farms using data included in the *2002 Census of Agriculture*. First, all farm entities must be a family organization[16] to be considered in the FSA eligible group. Then FSA eligible farms include family organizations with more than $500 in interest expenses on farm-related debt and annual sales in excess of $5,000. In addition, if farms have a principal operator under age 50 with fewer than 10 years farming experience, they are added to the FSA eligible group if not already included. Also, farms with principal operators who indicate farming as their primary occupation and who work fewer than 200 days off-farm are added to the FSA eligible group if not already included. Finally, if gross sales are from $5,000 to less than $10,000 and the principal operator works 200 or more days a year off-farm, the farm is deleted from FSA eligible farms unless the principal operator is under age 50 and has been farming less than 10 years. The goal of these criteria is to include small limited-resource family farms and beginning farmer startups while excluding hobby farms and low-debt farms since these two farm groups are considered less likely to be eligible for FSA direct loans.[17]

This method estimates 787,816 of 2,124,452 U.S. farms (37%) as potentially eligible for FSA direct loans (FSA eligible).[18] Figure 2 presents estimates of FSA eligible farms as a percentage of total farms by U.S. production region and selected cohorts. The FSA eligible farm percentages for the All Farms cohort range by region from 29% for the Southeast to 51% for the Northern Plains. For the All SDA cohort, the percentage of FSA eligible farms ranges from 27% for the Delta States region to 38% for the Mountain region.

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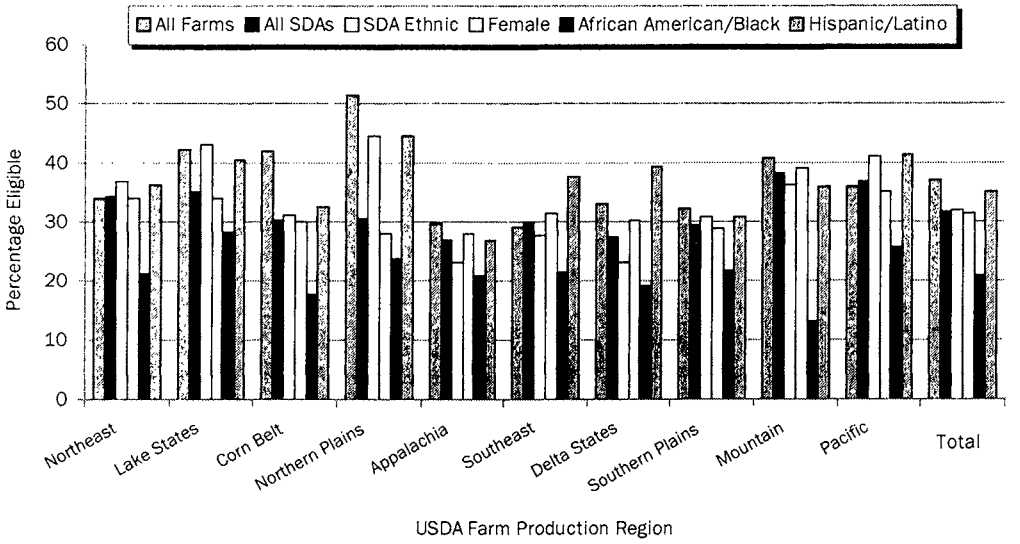
[15] The four-year period increases the number of data points used in the calculation. This approach is similar to the approach taken by Dodson and Koenig (2003) who used five years of county data in the numerator to increase the number of data points since many counties in their data set had little FSA lending activity during a given year. While there are 45,016 unique borrowers within years, some of these borrowers are not unique across years. Across years, there are 28,852 unique borrowers indicating that some borrowers originated loans in more than one year.

[16] To be a family organization, a farm has to be a family or individual operation, or a partnership, or a family-held corporation.

[17] The "Hobby Farm" criteria and nomenclature and the exclusion of low-debt farms are similar to those used by Dodson and Koenig (2003).

[18] This estimate is undoubtedly high since the eligibility criteria do not necessarily exclude farmers who could obtain credit elsewhere, and therefore be ineligible to receive FSA loans. However, the eligibility criteria do attempt to exclude hobby and low-debt farms as was done by Dodson and Koenig (2003).



Source: Computed from *2002 Census of Agriculture*

Figure 2. FSA Eligible Farms as a Percentage of Total Farms by Region and Selected Cohorts (2002)

Among the different cohorts presented in Figure 2, African American has the lowest percentage of FSA eligible farms for every region. In fact, many states are estimated to have no FSA eligible farms operated by African Americans including Alaska, Connecticut, Hawaii, Idaho, Maine, North Dakota, Rhode Island, Utah, and Vermont. The Hispanic/Latino cohort has the largest percentage of FSA eligible farms in the Southeast, Delta States, and Pacific regions when compared with other cohorts in those regions. The percentage of FSA eligible female farms is less than the percentage for All Farms in every region except the Southeast. These results lead us to expect some diversity in FSA loan numbers by cohort and region based on eligible borrower numbers and not necessarily due to loan program bias.

Family Farm Market Penetration

FSA's direct loan penetrations of the FSA eligible all family farm market for OL, FO, OL-FO combined, and all direct loans (OL-FO-EM combined) are 2.9%, 0.8%, 3.4%, and 3.7%, respectively, for the United States (Table 3). For all direct loans, the all family farm market penetration ranges by state from 0.4% in Delaware to 21.5% in Rhode Island. It is apparent that there is considerable state-level heterogeneity in FSA market penetration. State-level variations in penetration are likely due to differences in: (*a*) eligibility, (*b*) agricultural enterprise types, (*c*) agricultural economy health, (*d*) farm composition (i.e., states that typically have a greater proportion of "large" farms would not be as heavily served by FSA programs and thus will have a lower market penetration), (*e*) natural disaster occurrence, and (*f*) FSA direct loan obligation allocation and lending practice. The disparity in penetration rates is even more pronounced at the county level, ranging from 0% in 484 counties to 89% in Bristol County, Massachusetts.

Small Family Farm Market Penetration

FSA policy is concerned with helping smaller family farms. To measure how successfully this targeted market is served, a small family farm penetration rate is computed. Given that sales figures for direct loan borrowers are not available

Table 3. Penetration Percentages by Targeted Market, FY 2000–2003

Category	OL	FO	OL and FO Combined	OL, FO, and EM Combined
Small Family Farm [a]	3.11	0.81	3.58	3.86
BF Farm [b]	2.49	2.04	3.16	N/A [c]
SDA Farm	3.38 [b]	1.02 [b]	3.99 [b]	4.62 [d]
All Family Farms	2.93	0.76	3.37	3.66

Sources: 2002 Census of Agriculture, FSA New Loan data set, and FHP data.

[a] Numerator is estimated from combined NL and FHP data set and is based on assistance type.

[b] Numerator is based on loan assistance type (NL data set).

[c] N/A = not applicable; EM loans do not have SDA or BF loan assistance types.

[d] Numerator includes loans by SDA assistance type and non-SDA loans to women and ethnic/racial minorities (NL data set).

from the FSA NL data set, the market penetration rate numerator is estimated from the combined NL and FHP data set for FY 2000–2003. Small farms receiving FSA direct loans are those farms with gross income less than $250,000. If the proportion of farms in the FHP data set that are small is the same proportion of farms in the NL data set, 26,812 FSA borrowers have small family farms out of an estimated 694,859 FSA eligible small family farms. This results in a small family farm penetration rate of 3.9% for all direct loans (OL-FO-EM combined). The FSA small family farm penetration rates in the OL, FO, and OL-FO combined markets are 3.1%, 0.8%, and 3.6%, respectively (Table 3).

SDA Farm Market Penetration

Over the four-year FY 2000–2003 period, there were 4,040 SDA borrowers (OL-FO combined) in the United States based solely on loan assistance type. Therefore, the SDA OL and FO combined penetration rate numerator is 4,040. The SDA penetration rate denominator is 101,195 FSA eligible SDA farmers estimated from the *2002 Census of Agriculture* data. The penetration rate based on these numbers is 4%.

However, identifying SDA farmers solely on the basis of assistance type underestimates SDA market penetration. As noted earlier, there are women and racial/ethnic minorities who received EM loans or non-SDA assistance type loans. They are omitted in any SDA assistance type-based identification. The magnitude of this omission is estimated by identifying all SDA eligible applicants who received an FSA direct loan including EM loans for FY 2000–2003. There are 4,676 SDA borrowers when SDA assistance type and demographic data on gender and race/ethnicity are used to identify a borrower as SDA, which results in a penetration rate of 4.6% for all direct loans (Table 3).

Figure 3 illustrates FSA market penetration in the SDA market based solely on loan assistance type over the FY 2000–2003 period. Penetration rates are generally high in states where SDA borrowers are clustered, such as Louisiana, Oklahoma, and Arkansas. Higher concentrations of SDA farmers may lead to greater sensitivity by FSA management to make SDA loans and to potentially eligible applicants to apply for SDA loans. High penetration rates could also be obtained from states having relatively few SDA farms, such as Rhode Island which has an estimated 69 FSA eligible SDA farmers and a penetration rate of 23.2%.

Beginning Farmer Market Penetration

In order to characterize FSA beginning farmer market penetration, two sets of BF eligible farms are estimated from the *2002 Census of Agriculture* data to maintain

Sources: Computed from FSA New Loan Database and *2002 Census of Agriculture.*

Figure 3. FSA Direct SDA, FO, and OL Combined Market Penetration Percentage (FY 2000–2003)

Sources: Computed from FSA New Loan Database and *2002 Census of Agriculture.*

Figure 4. FSA Direct Beginning Farmer FO and OL Combined Market Penetration Percentage (FY 2000–2003)

consistency with mandated beginning farmer definitions. The first set pertains to OL eligible farms and consists of FSA eligible farmers with 10 years or less of farming experience. The second set corresponds to FO eligible farms and consists of FSA eligible farmers with 3–10 years farming experience and owning acreage less than or equal to 30% of the county average farm size.

Figure 4 portrays FSA penetration rates in the BF market (OL-FO combined) for FY 2000–2003. The "market" for the penetration rate denominator is BF OL eligible farms. The BF OL eligible farm is a less restrictive beginning farmer definition than BF FO, and it is appropriate as a denominator since the numerator is a combination of BF OL and BF FO borrowers. The estimated penetration rate ranges from 0.5% to 20.1%. Excluding the 20.1% penetration rate for Rhode Island reduces the upper limit of the range to 10%. Even considering the reduced range, there is still great market penetration variability across states.

Penetration Rate Comparisons and Funding Effects

The market penetration estimates for the various FSA direct loan markets targeted may appear small, ranging from 0.8% to 4.6% (Table 3). However, it must be remembered these rates are based on new loan originators only. ARMS data may be used to estimate the number of farmers holding any FSA direct loans, new (originated during FY 2000–2003) or old (originated prior to FY 2000). When this is done, the estimated number of new originators plus old originators is about five times the new originators number. Thus, if penetration is viewed as percentage of the market holding any FSA direct loan, the rates would increase by roughly a factor of five.

FSA small family, BF, and SDA farmer loan targeting has likely resulted in these groups obtaining more credit than they would have obtained from FSA without targeting. For instance, the small family farm market penetration rate for all direct loans is 3.9% compared with 3.7% for the all family farm market (Table 3). Although FSA does not explicitly reserve loan funds for farms with annual sales less than $250,000, FSA loans are more likely to meet the credit needs of these small farms than other larger farms because of the caps on FSA direct farm loan program indebtedness.

Beginning farmers have likely benefited from targeting, especially in FO loans where the penetration rate is 2% compared with 0.8% for all family farms. SDA farmers seem to have benefited most from OL loan targeting since its 3.4% penetration rate is the highest rate for OL loans among the borrower groups. The relatively higher overall (FO-OL-EM combined) SDA penetration rate of 4.6% compared with the all family farm rate of 3.7% suggests targeting has been successful at directing loans to disadvantaged groups (Table 3). For all farm groups, FO market penetration is less than OL market penetration, probably due to the lower proportion of FO loans to total loans made.

FSA lending authority is a major limiting factor in market penetration levels. FSA frequently obligates nearly all funds it is authorized to lend. With the exception of FY 2000 when only 73% of lending authority was obligated, 95% to 100% of lending authority was obligated by the end of each fiscal year for 2000–2003. Consequently, for FSA to make more loans than it is currently making, FSA would need additional lending authority so more funds would be available to serve additional farmers at the same average loan size. Barring a lending authority increase, a reallocation of funds may be necessary to increase certain targeted market penetrations. Recall 35% of OL funds and 70% of FO funds are targeted to beginning farmers, thus restricting funds available to non-beginning farmers, including those SDA farmers who are not beginning farmers.

Comparative Financial Characteristics: Is Targeting Financially Necessary?

The previous section addressed the question of FSA's success in serving the family farm market. The necessity of targeting FSA direct loans based on financial characteristics is addressed here. Farm operators capable of obtaining credit from commercial sources should not receive FSA direct loans. Hence, the financial characteristics of FSA borrowers should be distinctly inferior to those borrowers receiving credit from commercial sources, which would indicate FSA is directing loans to farmers in need of FSA loan assistance. To determine if such differences exist, the financial characteristics of FSA and non-FSA borrowers potentially eligible for FSA loans are compared using ARMS data.[19]

SDA and BF borrower groups specifically targeted to receive FSA loans may have different financial characteristics than nontargeted groups. Any differences may or may not support the targeting of FSA direct loans to SDA and BF borrower groups as financially necessary. ARMS data are used to compare these targeted groups with nontargeted groups independently of the farmers having or not having FSA direct loans. FHP data are subsequently used when comparing targeted groups and nontargeted groups for actual FSA borrowers.

The comparative financial strengths of the various borrower groups are measured by the following five financial characteristics:

- *Solvency.* This characteristic is measured by the debt-to-asset ratio which is computed by dividing borrowers' debts by assets.[20]
- *Liquidity.* Liquidity is measured by the current ratio which is computed by dividing current assets by current liabilities.
- *Profitability.* This characteristic is measured by the rate of return on assets which is computed for the FHP data by planned net farm income minus planned family living expenses all divided by total assets.
- *Repayment Capacity.* This trait is measured by the term debt coverage ratio when using ARMS data which is computed by dividing net farm income plus off-farm income plus depreciation plus interest minus estimated income tax expense minus family living expenses by scheduled principal and interest payments. A similar measure of repayment capacity when using FHP data is computed by dividing the balance available to service principal and interest payments by the total amount of principal and interest payments due in the current year.
- *Financial Efficiency.* Financial efficiency is measured by the asset turnover ratio which is computed by dividing gross farm income by farm assets.

Under normal conditions, a borrower's financial strength is expected to be inversely related to the debt-to-asset ratio and directly related to the current ratio, rate of return on assets, term debt coverage ratio, and asset turnover ratio.

FSA Eligible Farmers

Selected financial characteristics for U.S. farm operators identified as potentially eligible for FSA direct loans (FSA eligible) are obtained using 2000–2003 ARMS data

[19] ARMS data are the only national data available for such a comparison. Although detailed financial information on FSA borrowers is available for many FSA borrowers in the FHP data, it is problematic to use FHP data to compare with ARMS data on non-FSA borrowers. The difficulty is ARMS financial data are gathered as of year's end whereas FHP data can be collected at any time of the year. Moreover, ARMS and FHP financial variable definitions are somewhat different.

[20] Farm assets and farm debts are used for ARMS data, and total farm and nonfarm assets and debts are used for FHP data.

Table 4. Financial Characteristics of FSA Eligible Farms by Debt Source, 2000–2003 Average

Description	FSA New Recipient	Non-FSA Recipient	*t*-Value
Estimated Number of Farms	9,045	793,520	
Farm Operation Income Statement:			
Gross Cash Income ($)	208,877	140,127	1.97
	(31,797)	(14,185)	
Cash Expenses ($)	173,537	113,615	2.18*
	(25,362)	(10,622)	
Net Cash Farm Income ($)	35,350	26,513	0.85
	(9,675)	(3,913)	
Net Farm Income ($)	31,217	21,554	1.18
	(7,841)	(2,397)	
Farm Operation Balance Sheet:			
Farm Assets ($)	746,152	700,325	0.47
	(79,342)	(54,943)	
Farm Liabilities ($)	240,985	122,910	4.39*
	(25,375)	(8,954)	
Farm Equity ($)	505,167	577,415	-0.97
	(58,714)	(46,414)	
Farm Operation Financial Ratios:			
Current Ratio	1.90	22.72	-4.04*
	(0.34)	(5.14)	
Debt-to-Asset Ratio (%)	36.63	22.69	3.69*
	(2.69)	(2.65)	
Term Debt Coverage Ratio	4.17	7.26	-1.50
	(1.88)	(0.81)	
Asset Turnover Ratio	0.32	0.42	-1.31
	(0.03)	(0.07)	

Source: Computed from ARMS data.

Notes: The *t*-values followed by an asterisk (*) indicate mean differences are significant at the 5% level at 28 degrees of freedom and a critical *t*-value of 2.048 (two-tailed test). Standard error estimates (in parentheses) are computed using a jackknife procedure.

(Table 4).[21] Those classified as FSA new recipients are FSA eligible farms receiving at least one FSA-sourced direct loan in the calendar year of the ARMS survey. Those classified as non-FSA recipients are FSA eligible farms in the ARMS data not reporting any FSA-sourced direct loans.[22]

Standard errors are computed using the delete-a-group jackknife procedure (Dubman, 2000). To evaluate whether or not the observed differences between means are statistically significant, *t*-statistics at the 5% significance level (two-tailed) and 28 degrees of freedom with a critical *t*-value of 2.048 are computed for each of the two-way comparisons.[23]

[21] We compare FSA eligible farmers as defined earlier (as opposed to all farmers) in order to exclude hobby farms and low-debt farms similarly to Dodson and Koenig (2003).

[22] Analysis on farms classified as FSA old recipients is also available (see Nwoha et al., 2005). FSA old recipients are eligible farms reporting FSA-sourced direct loans but not listing any FSA-sourced loans originated in the calendar year of the ARMS survey. The analysis is not reported here because this article emphasizes identifying the characteristics of recent (new) recipients and determining if these characteristics support FSA direct loan targeting.

[23] The test statistics do not have exactly a *t*-distribution, but the critical value is more conservative than assuming a standard normal distribution.

Compared with nonrecipients, the FSA new loan recipients have more gross cash income, cash expenses, net cash farm income, and net farm income, although cash expenses is the only statistically significant difference. While FSA new borrowers have slightly higher (6%) assets, they also have accumulated significantly more (96%) liabilities, making their farm equity 13% lower than for the nonrecipients.

FSA new loan recipients have higher debt-to-asset ratios (indicating lower solvency and higher financial leverage) than non-FSA borrowers on average and this difference is statistically significant. The new recipients have an average debt-to-asset ratio of 36.6%, while non-FSA recipient farms have a debt-to-asset ratio of 22.7%. Liquidity is another financial characteristic where FSA new loan recipients lag their non-FSA counterparts. FSA new loan recipients have significantly less liquidity as indicated by their average current ratio of 1.9 relative to 22.7 for non-FSA recipients. In addition, FSA new loan recipients have less repayment capacity and less financial efficiency than non-FSA recipients as measured by average term debt coverage and asset turnover ratios, although these differences are not statistically significant (Table 4).

The comparative financial characteristics indicate FSA new loan recipients are distinct from non-FSA recipients. Although there are no statistically significant income differences, FSA new loan recipients are clearly much more in debt and, potentially, financially stressed as indicated by their significantly less solvency and liquidity compared to non-FSA recipients. Farmers having relatively low solvency and liquidity are more likely to be denied credit from commercial sources, and are therefore more likely to need to rely on FSA assistance.

SDA, BF, and Other FSA Eligible Farmers

ARMS data for FSA new loan recipients cannot be used to draw reliable inferences about how the financial characteristics of specifically targeted farmers (SDA and BF) differ from non-targeted farmers (non-SDA and non-BF) because too few SDA and BF farms with new FSA loans are sampled in ARMS. However, ARMS data can be used (as is done here) to test for financial characteristic differences between targeted and nontargeted FSA eligible farms independently of whether the farms did or did not receive FSA loans.

SDA and Non-SDA

Three SDA farm types are considered here in evaluating the financial need for targeting FSA direct loans. They include SDA race (farms where the primary operator is non-white), SDA gender (farms where the primary operator is female), and non-SDA (farms where the primary operator is white and male).

Financially, SDA race farms appear to be similar to non-SDA farms (Table 5). Although SDA race farms are estimated to be smaller in size—i.e., they have less gross cash income, cash expenses, net cash income, net farm income, farm assets, farm liabilities, and farm equity than non-SDA farms on average—the differences are not significant. In addition, there are no significant differences in financial ratio means for SDA race farms and non-SDA farms.

On average, the income statement of SDA race farms is significantly superior to that of SDA gender farms. The SDA race farms' average gross cash income and net cash farm income are significantly higher than those of the average SDA gender farm by 115% and 293%, respectively. Although the balance sheet for the average SDA race farm also appears to be stronger with more farm assets, liabilities, and equity than the average SDA gender farm, the differences are not significant. Likewise, the differences in the financial ratios indicating solvency, liquidity, repayment capacity, and financial efficiency for SDA race and SDA gender farms are not statistically significant.

Table 5. Financial Characteristics of FSA Eligible Farms by SDA Status, 2000–2003 Average

	SDA Status			*t*-Value		
Description	**SDA Race (a)**	**SDA Gender (b)**	**Non-SDA (c)**	**a–b**	**a–c**	**b–c**
Estimated Number of Farms	47,450	56,688	778,964			
Farm Operation Income Statement:						
Gross Cash Income ($)	132,830	61,677	148,083	2.27*	-0.45	-4.65*
	(29,836)	(9,673)	(15,870)			
Cash Expenses ($)	107,127	55,130	119,509	1.77	-0.40	-4.57*
	(28,336)	(7,516)	(11,932)			
Net Cash Farm Income ($)	25,703	6,547	28,574	2.09*	-0.30	-3.95*
	(8,490)	(3,491)	(4,355)			
Net Farm Income ($)	22,114	8,055	22,896	1.32	-0.07	-3.37*
	(10,088)	(3,463)	(2,731)			
Farm Operation Balance Sheet:						
Farm Assets ($)	617,343	514,100	715,613	1.22	-1.11	-2.62*
	(67,593)	(51,292)	(57,367)			
Farm Liabilities ($)	111,230	73,031	132,096	2.03	-1.09	-4.22*
	(16,181)	(9,610)	(10,179)			
Farm Equity ($)	506,113	441,069	583,517	0.85	-1.00	-2.17*
	(61,577)	(45,302)	(47,503)			
Farm Operation Financial Ratios:						
Current Ratio	15.46	37.42	20.59	-1.65	-0.83	1.21
	(3.39)	(12.91)	(5.16)			
Debt-to-Asset Ratio (%)	17.38	16.02	23.87	0.38	-1.69	-2.21*
	(2.72)	(2.28)	(2.72)			
Term Debt Coverage Ratio	6.63	4.87	7.12	0.45	-0.18	-0.74
	(2.63)	(2.93)	(0.83)			
Asset Turnover Ratio	0.38	0.44	0.41	-0.21	-0.15	0.14
	(0.19)	(0.24)	(0.07)			

Source: Computed from ARMS data.

Notes: The *t*-values followed by an asterisk (*) indicate mean differences are significant at the 5% level at 28 degrees of freedom and a critical *t*-value of 2.048 (two-tailed test). Standard error estimates (in parentheses) are computed using a jackknife procedure.

The largest and most significant differences among the three SDA types are between SDA gender farms and non-SDA farms. SDA gender farms are significantly smaller in size when measured by farm assets, liabilities, equity, and gross farm income, and they have less net cash farm income and net farm income than non-SDA farms. Although these size and income differences may imply that SDA gender farms have inferior financial characteristics, this is countered by SDA gender farms having significantly higher solvency (lower debt-to-asset ratio) than non-SDA farms.

BF and Non-BF

The average BF eligible income statement and balance sheet variables differ substantially and significantly from those of the average non-BF eligible farm (Table 6). As expected, beginning farms are much smaller in financial size than non-beginning farms by about $150,000 in mean gross cash income. The average OL eligible beginning farm has 26.1% of the gross cash income, 29% of the cash expenses, 15% of the net cash farm income, and 23% of the net farm income of the average non-BF eligible farm. In addition to being much smaller in income

Table 6. Financial Characteristics of FSA Eligible Farms by Beginning Farm Status, 2000–2003 Average

	Beginning Farm Status			t-Value		
Description	**BF OL Eligible (a)**	**BF FO Eligible (b)**	**Non-BF Eligible (c)**	**a–b**	**a–c**	**b–c**
Estimated Number of Farms	334,868	176,575	497,351			
Farm Operation Income Statement:						
Gross Cash Income ($)	52,537	46,414	201,045	0.50	-10.27*	-14.71*
	(11,137)	(5,031)	(9,231)			
Cash Expenses ($)	46,460	41,405	160,150	0.52	-10.21*	-14.76*
	(8,726)	(4,093)	(6,924)			
Net Cash Farm Income ($)	6,078	5,009	40,895	0.34	-7.87*	-9.08*
	(2,610)	(1,694)	(3,571)			
Net Farm Income ($)	7,184	6,714	31,542	0.21	-7.60*	-7.69*
	(1,549)	(1,591)	(2,808)			
Farm Operation Balance Sheet:						
Farm Assets ($)	352,699	219,767	933,195	1.72	-7.41*	-31.58*
	(76,050)	(12,624)	(18,732)			
Farm Liabilities ($)	65,983	43,381	169,356	1.83	-8.40*	-19.03*
	(11,414)	(4,758)	(4,604)			
Farm Equity ($)	286,716	176,386	763,839	1.65	-7.01*	-31.74*
	(66,244)	(9,850)	(15,669)			
Farm Operation Financial Ratios:						
Current Ratio	35.12	31.54	13.00	0.30	2.35*	1.79
	(7.90)	(8.99)	(5.10)			
Debt-to-Asset Ratio (%)	27.35	30.09	20.69	-0.22	1.00	0.89
	(6.60)	(10.50)	(0.64)			
Term Debt Coverage Ratio	5.35	7.88	7.70	-0.43	-0.75	0.03
	(2.75)	(5.14)	(1.50)			
Asset Turnover Ratio	0.52	0.57	0.33	-0.18	1.09	1.26
	(0.17)	(0.18)	(0.03)			

Source: Computed from ARMS data.

Notes: The *t*-values followed by an asterisk (*) indicate mean differences are significant at the 5% level at 28 degrees of freedom and a critical *t*-value of 2.048 (two-tailed test). Standard error estimates (in parentheses) are computed using a jackknife procedure.

terms, BF OL eligible farms are much smaller in terms of farm assets, liabilities, and equity, with only 38%, 39%, and 38%, respectively, of the non-BF eligible farm amounts. The financial differences between BF FO eligible farms and non-BF eligible farms are even greater.

The significantly lower asset, liability, equity, and income levels indicate BF eligible farmers have the characteristics expected of less experienced farmers and the BF program is targeted to a class of farmers distinctly different from those farmers who are FSA eligible but do not qualify as beginning farmers. The average net farm income of BF OL eligible farmers is $7,184, which is less than half the 2003 U.S. federal poverty threshold of $15,260 for a family with three members (U.S. Department of Health and Human Services, 2003), such that off-farm income is necessary to generate sufficient income to support a family. With such meager farm income and limited farm assets and equity, beginning farmers are likely to be turned down for commercial loans. Therefore, it appears targeting this group can be justified in terms of financing farmers with limited financial resources.

Table 7. FSA Borrower Financial Ratio Medians by Cohort, FY 2000–2003

Cohort	N	Debt-to-Asset Ratio	Current Ratio	Return on Assets	Debt Coverage Ratio
BF	7,177	0.74	0.84	0.13	1.04
Non-BF	11,976	0.64	0.68	0.08	1.03
SDA	2,664	0.67[a]	0.57	0.08	1.04
Non-SDA	16,489	0.68[a]	0.75	0.10	1.03

Source: FHP data set.

[a] Estimated medians are statistically different for BF vs. Non-BF and SDA vs. Non-SDA for all financial ratio variables except the SDA vs. Non-SDA debt-to-asset ratio. Nonparametric tests for location and scale differences estimated via the NPAR1WAY procedure in SAS™ are used to determine statistical significance.

FSA Direct Loan Borrower Groups

The combined NL and FHP data set is used in computing financial ratios to represent the financial characteristics of farmers who received FSA direct loans during FY 2000–2003. Table 7 reports the median financial ratios of these farmers based on BF and SDA status. BF borrowers have a higher debt-to-asset ratio, current ratio, return on assets, and debt coverage ratio than non-BF borrowers, which correspond to less solvency, greater liquidity, higher profitability, and more repayment capacity. These differences indicate BF borrowers are financially stronger than non-BF borrowers, except in the area of solvency. But both groups generally have weak financial characteristics, particularly for solvency and liquidity. For example, both groups are less solvent and have more financial risk than all U.S. farms on average. The debt-to-asset ratio of FSA direct loan borrowers is higher than the average debt-to-asset ratio of 0.15 for all U.S. farms during the same four-year period.[24] Also, the majority of FSA borrowers may be considered illiquid since the median current ratio is less than one.

The FSA borrower return on assets and debt coverage ratios may appear adequate since they are positive and greater than one, respectively. However, it should be noted that these ratios rely on individual borrower and FSA farm loan manager forecasts (plans) of next year's income and expenses for the farm, whereas the debt-to-asset and current ratios rely on actual balance sheet data taken prior to loan origination. Therefore, if borrower and FSA farm loan manager forecasts are overly optimistic, the return on assets and repayment ratios would be biased upward. It could be hypothesized BF borrowers are more likely than non-BF borrowers to have overly optimistic forecasts, since BF borrowers are less likely than non-BF borrowers to have actual income and expense records from previous years to develop more reliable forecasts. In any event, FSA borrowers, both BF and non-BF, have relatively weak financial characteristics.

It can be argued that either SDA borrowers or non-SDA borrowers have stronger financial characteristics depending on the financial characteristic considered. SDA borrowers have a smaller current ratio (less liquidity) and return on assets (less profitability) but a higher debt coverage ratio (more repayment capacity) than non-SDA borrowers. And, the difference in debt-to-asset ratio (solvency) between SDA and non-SDA borrowers is statistically insignificant. As was the case for BF and non-BF farmers with FSA loans, both SDA and non-SDA borrower groups are likely to be less solvent, more financially risky, and less liquid than farmers without FSA loans.

[24] The U.S. debt-to-asset ratio only includes farm debts and farm assets as opposed to total farm and nonfarm debts and assets in the FHP (USDA/ERS, 2006).

Summary and Conclusions

The Farm Service Agency's direct farm loan program is mandated to provide credit to farmers unable to obtain credit from conventional sources at reasonable rates and terms. By setting eligibility guidelines at levels that screen out corporate and hobby type farms, federal legislation attempts to channel FSA program funds for use by family farms. In addition, a portion of direct loan funds are specifically reserved for socially disadvantaged and beginning farmer applicants.

By most measures, the targeting of FSA direct loans to small family, SDA, and beginning farms appears successful. Small family farms received a majority (78–92%) of new FSA direct loans originated in FY 2000–2003, where "small" refers to farms with sales less than $250,000. Nearly 14% of new direct loans went to SDA farmers, and the percentages were much higher in states with higher concentrations of SDA farmers, as would be expected. Another targeted group, beginning farmers, received large shares of direct farm loan volumes with 39% of OL loan and 69% of FO loan volumes—closely matching the initial fund targets of 35% and 70% in each fiscal year.

SDA farms appear to have been assisted by FSA targeting, since 4.6% of FSA eligible SDA farms received direct loans compared with 3.7% of all FSA eligible family farms. BF farms also appear to have been assisted by FSA targeting, although the BF penetration rate of 3.2% was less than the 3.4% for all FSA eligible family farms. The penetration difference is to a great extent due to the large number of eligible farms classified as beginning farmers in the penetration denominator. Also, the penetration difference is partially due to some BF eligible farms receiving non-BF assistance type loans and not being included in the penetration numerator. The particularly high level of FO loan funds targeted to BF farms explains the greater penetration by FSA into the BF FO loan market than into the SDA FO and all family farm FO loan markets.

In general, FSA borrowers were in a weaker financial position than eligible non-FSA borrowers by virtue of significantly higher cash expenses, debt levels, and debt-to-asset ratios and lower current ratios. The differences between FSA eligible SDA race farms and non-SDA farms were not statistically significant. FSA eligible SDA gender farms were significantly smaller than non-SDA farms when size was measured by gross farm income, net cash farm income, net farm income, and farm assets, liabilities, and equity. These differences indicate SDA gender farms had inferior financial characteristics; however, one major exception was that SDA gender farms had lower debt-to-asset ratios, which indicates a superior financial characteristic. The differences in income statement and balance sheet variable means between FSA eligible BF farms and non-BF farms suggest the BF program has been targeted to a class of farmers unlikely to qualify for commercial credit. While comparative financial characteristics of borrower groups (SDA vs. non-SDA and BF vs. non-BF) with FSA loans produced mixed results, all the measures indicated FSA borrowers were weaker than non-FSA borrowers.

Within the scope of the analysis presented in this article, the results are consistent with FSA success in meeting its mandate of serving family farms and targeting SDA and BF farms. Considering the financial characteristics comparisons presented, it appears most FSA direct loan recipients would have been denied commercial credit, revealing a need for FSA loan assistance. Also, the significantly weaker financial characteristics of beginning farms relative to non-beginning farms indicate targeting of FSA funds may be needed to successfully serve beginning farms. However, the lack of significant financial characteristic differences between SDA race farms and non-SDA farms and the mixed inferences from significant financial characteristic differences between SDA

gender and non-SDA farms (with SDA gender farms being smaller and having less income, yet greater relative solvency) call into question the necessity of targeting FSA funds to SDA farms based solely on financial differences. Obviously, other social and economic objectives are advanced by targeting the SDA farm market.

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Efficiency Differences of U.S. Agricultural Banks

Onelack Choi, Spiro E. Stefanou, and Jeffrey R. Stokes

Abstract

A balanced panel data set covering 519 U.S. agricultural banks is constructed for the period 1996–2005. Cost efficiency measures of agricultural banks obtained from stochastic frontier analysis and data envelopment analysis are regressed on various bank-specific characteristics to explain the cost efficiency differences of agricultural banks. The results indicate that (*a*) cost efficiencies are positively related to profitability while negatively related with the raw cost inefficiency measure, (*b*) older agricultural banks tend to be more efficient, (*c*) regulation may deteriorate efficiency levels, (*d*) bigger agricultural banks tend to be less efficient, (*e*) bank-specific characteristics can explain DEA efficiency scores better than they can SFA efficiency measures, and (*f*) the inconsistency issue related to two-step approaches is not serious.

Key words: agricultural bank, data envelopment analysis, efficiency, efficiency differences, stochastic frontier analysis

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In recent years, the banking sector has been characterized by ongoing consolidation through mergers and acquisitions. One reason for this trend was the bank failures occurring during the 1980s and the incentives for surviving banks to become more efficient. Over the same time period, technological innovation and regulatory change have conspired to change the structure of banking. Recent examples of such regulatory change include the Riegel-Neal Interstate Banking and Branching Efficiency Act and Basle Committee recommendations on minimum bank capital.

The agricultural sector has not been immune to these changes. Following the farm financial crisis of the 1980s, commercial banks assisted in more fully meeting the credit needs of agricultural borrowers. Similarly, the Farm Credit System reorganized in an effort to become a more efficient supplier of agricultural credit, and the advent of the Federal Agricultural Mortgage Corporation brought the innovation of mortgage securitization to the agricultural sector.

Numerous studies have focused on determining the extent to which banks are efficient in delivering credit. Even so, few studies have undertaken the task of assessing efficiency patterns over time, which is important for understanding the extent to which regulation and innovation impact banking efficiency and provide a precursor to identifying how banks actually become more efficient in delivering credit. An example is the impact of the Basle Committee's recommendations regarding the minimum amounts of capital banks must hold. While there are studies arguing that this minimum capital

recommendation can lead to either increased or decreased bank risk taking, the observed impact of the Basle Committee's recommendations on bank risk taking is mixed. It is possible that minimum capital ratios have had the unintended consequence of changing the allocative efficiency of the bank despite their capacity to reduce the credit risk facing the bank. For example, Berger, Herring, and Szego (1995) note that regulatory capital has had an ambiguous effect on bank risk taking.

In this article, we focus on explaining efficiency differences among U.S. agricultural banks and examining the impact bank-specific characteristics have on efficiency changes. One- and two-step approaches using stochastic frontier analysis (SFA) and data envelopment analysis (DEA) are used to explain the differences in cost efficiency levels among agricultural banks. In a two-step approach, efficiencies of banks are first evaluated using a frontier estimation approach. The cost-efficiency estimates are then regressed on firm-specific characteristics. Pairwise correlation analyses are incorporated within the second step since causation between cost efficiency and each bank-specific characteristic may be mutual.

Battese and Coelli (1993) demonstrate that two-step approaches yield inconsistent estimates when some firm-specific characteristics are determinants of efficiency measures. They recommend one-step estimation approaches in which firm-specific characteristics as well as input prices and outputs (for a cost frontier), or inputs (for a production frontier) determine efficiency measures. Both two-step and one-step approaches are used to disentangle factors explaining banking efficiency differences.

In the next section we review the banking efficiency literature and the emerging pattern of results. This is followed by the cost function specification and estimation of cost efficiency for U.S. agricultural banks and the decomposition of cost efficiency. The results from the one- and two-step approaches are compared to address the differences in efficiency levels, followed by an assessment of the impacts of bank-specific characteristics on the types of cost-efficiency changes. The paper concludes with some comments and implications of these results.

Literature Review

Ferrier and Lovell (1990); Kaparakis, Miller, and Noulas (1994); Mester (1996); and Kraft and Tirtiroglu (1998) utilize SFA to examine bank efficiency. Ferrier and Lovell (1990) analyze 575 U.S. banks participating in the Federal Reserve System's Functional Cost Analysis (FCA) Program in 1984. Their findings show there is no apparent trend in the cost of inefficiency as bank size grows. Technical inefficiency raises costs nearly 9% on average, while allocative inefficiency tends to raise costs by 17%.

Kaparakis, Miller, and Noulas (1994) analyze 5,548 banks using 1986 Call Report data. Employing a flexible stochastic frontier specification, they find that average inefficiency rises with bank size; in particular, the largest banks are nearly twice as inefficient as the most efficient group with assets between $75 and $150 million. Upon obtaining inefficiency measures, they introduce portfolio, bank structure, and regulatory constraint variables to explain the inefficiency differences across banks. The authors conclude that the operation of a branch network, either domestic or foreign, contributes to higher cost inefficiency, and that increasing risk of operation is associated with higher cost inefficiency.

Kraft and Tirtiroglu (1998) employ data obtained from the audited final accounts of commercial banks in Croatia. The cost efficiency and scale efficiencies are estimated for old and new, state and private banks. New banks are found to be more inefficient than either old privatized banks or old state banks.

Some recent studies evaluating the impact of deregulation have focused on the Spanish banking industry. Tortosa-Ausina (2002) reports decreasing inefficiencies in the face of deregulation when a firm's efficiency scores are compared to those with similar specializations. Likewise, Kumbhakar and Lozano-Vivas (2005) found total factor productivity growth responded positively to deregulation.

Berger and Humphrey (1991) and Berger (1993) adopt thick frontier analysis (TFA) which identifies the lowest cost quartile as a "thick frontier." The estimated frontier is assumed to be the efficient subgroup. Other subgroups are then compared to this efficient subgroup. While this approach is not precise, the assumptions are less restrictive than those of SFA. Analyzing inefficiencies for all U.S. banks in 1984, Berger and Humphrey (1991) conclude that inefficiences measured relative to a thick frontier cost function dominate measured scale and product mix economies. They also find that technical inefficiencies dominate allocative inefficiencies. In a related study, Berger (1993) examines bank inefficiencies using panel data over 28,000 observations on U.S. banks from 1980 to 1989 and reports managerial differences in efficiency are important in banking while scale efficiency differences are not.

DEA based on the linear programming framework is a popular approach to studying banking efficiencies. Rangan, Grabowski, and Pasurka (1988) use a random sample of 215 banks drawn from Call Report data for the end of 1986. Based on their findings, these banks could have produced the same level of output with only 70% of the inputs actually used, and most of this inefficiency is due to pure technical inefficiency rather than scale inefficiency. Further, their regression analysis shows that the technical inefficiency of the banks is positively related to size and negatively related to product diversity.

Weber and Devaney (1999) focus on 247 sample banks using DEA to identify the loss in real estate lending due to risk-based capital standards. After decomposing overall technical efficiency into pure technical efficiency, regulatory efficiency, and scale efficiency, the lost real estate lending from the implementation of risk-based capital standards is 2.7% of total bank assets and the decline in regulatory inefficiency results from increases in bank equity capital and a slower growth in real estate lending relative to lower risk securities investment.

Studies such as those conducted by Ferrier and Lovell (1990) and Resti (1997) use both SFA and DEA, and compare separately obtained efficiency results to each other. Comparing results from DEA and SFA using 1986 Call Report information, Ferrier and Lovell report that the two technical efficiency rankings obtained from DEA and SFA are positively correlated although the correlation coefficient is not statistically significant. Using a balanced panel of 270 Italian banks, Resti finds high positive correlation between efficiencies measured by DEA and SFA, and notes that DEA and SFA results do not differ dramatically when they are based on the same data.

Bauer et al. (1998) evaluate and compare estimates of U.S. bank efficiency measures obtained from various approaches using data from 683 U.S. banks over the period 1977–1988. Their findings show the parametric and nonparametric results are not consistent. In general, the DEA approach yields much lower average efficiencies, while SFA and TFA approaches yield relatively high efficiency measures—suggesting the use of multiple techniques and specifications is likely to be helpful in performing regulatory analysis.

Evanoff and Israilevich (1991) present a summary of adopted approaches and empirical results for banking efficiency. Overall inefficiency measures obtained in most banking efficiency studies range from 20% to 30% with allocative inefficiencies in

the range of 1% to 15%. These inefficiency ranges indicate that allocative inefficiency is relatively minor compared to technical inefficiency.

A brief summary of earlier efficiency comparisons can be found in Bauer et al. (1998), who report that rank-order correlations between DEA and SFA are contradictory. In contrast to Resti's (1997) findings of very high rank-order correlations ranging from 0.73 to 0.89, Ferrier and Lovell (1990) found very low (0.02) correlation. Berger and Mester (1997) use a two-step procedure to examine several possible sources of the differences in measured efficiency. As second-step explanatory variables, they introduce bank size, other bank characteristics, market characteristics, and state geographic restrictions, and conclude that a number of these factors appear to influence efficiency levels.

In the agricultural economics literature, Ellinger and Neff (1993) discuss issues related to the measurement of agricultural banking efficiency and the merits of stochastic frontier analysis and DEA. Their empirical application suggests that the two methods can result in very different estimates of inefficiency. Using the same data set of agricultural banks, Featherstone and Moss (1994) and Neff, Dixon, and Zhu (1994) conclude that economies of scale are exhausted at mean bank size, economies of scope are nonexistent, and profit inefficiencies generally decline with bank size.

In a more recent study, Dias and Helmers (2001) employ DEA and estimate an output-oriented Malmquist index to determine that the primary source of productivity improvements for larger banks has been technical change and innovation. Small banks, on the other hand, derive competitive strength from increased efficiency gains or catching up with frontier banks. In addition, their results also suggest that competitive pressure from 1981 to 1991, brought about by some of the restructuring occurring in the agricultural credit market during that period, led to an increase in productivity growth volatility.

In summary, DEA usually yields lower average efficiencies than SFA because DEA regards random errors as part of measured inefficiencies. The implications from efficiency comparison studies are mixed. Some found high rank-order correlations between efficiency measures generated by DEA and SFA while others found very low correlations. Some studies seek to explain possible sources of differences in measured efficiency.

Methodology

Cost Inefficiency Measurement Using the Stochastic Cost Frontier Approach

Following Kumbhakar and Lovell (2000), we define the cost efficiency (*CE*) of bank *j* at time *t*, CE_{jt}, as:

$$(1) \quad CE_{jt} = \frac{C(y_{jt}, w_{jt})e^{v_{jt}}}{E_{jt}},$$

where E_{jt} represents the expenditure incurred by bank *j* at time *t*, y_{jt} is the output produced by bank *j* at time *t*, and w_{jt} is the vector of input prices for bank *j* at time *t*. The term $C(y_{jt}, w_{jt})e^{v_{jt}}$ represents the stochastic cost frontier at time *t*, where v_{jt} is the two-sided error denoting a random production shock for bank *j* at time *t*.

Introducing a one-sided error term $u_{jt}(u_{jt} \geq 0)$, the expenditure function can be written as:

$$(2) \quad E_{jt} = C(y_{jt}, w_{jt})e^{u_{jt}}e^{v_{jt}}.$$

Taking natural logs for both sides of equation (2) yields:

$$(3) \quad \ln(E_{jt}) = \ln(C(y_{jt}, w_{jt})) + u_{jt} + v_{jt}.$$

Assuming that the deterministic part of the cost frontier takes a translog form, (3) can be rewritten as:

$$(4)\quad \ln(E_{jt}) = \beta_{0t} + \beta_y \ln(y_{jt}) + \sum_{i=1}^{n} \beta_i \ln(w_{ijt}) + \tfrac{1}{2}\beta_{yy}\ln(y_{jt})^2 + \sum_{i=1}^{n} \beta_{iy}\ln(w_{ijt})\ln(y_{jt}) + \tfrac{1}{2}\sum_{k=1}^{l}\sum_{i=1}^{n} \beta_{ki}\ln(w_{kjt})\ln(w_{ijt}) + u_{jt} + v_{jt}.$$

Denoting β_{jt} as $\beta_{0t} + u_{jt}$, (4) can be rewritten as:

$$(5)\quad \ln(E_{jt}) = \beta_{jt} + \beta_y \ln(y_{jt}) + \sum_{i=1}^{n} \beta_i \ln(w_{ijt}) + \tfrac{1}{2}\beta_{yy}\ln(y_{jt})^2 + \sum_{i=1}^{n} \beta_{iy}\ln(w_{ijt})\ln(y_{jt}) + \tfrac{1}{2}\sum_{k=1}^{n}\sum_{i=1}^{n} \beta_{ki}\ln(w_{kjt})\ln(w_{ijt}) + v_{jt}.$$

Estimation of equation (5) with the restriction for the homogeneity of degree +1 in input prices,

$$\sum_{i=1}^{n} \beta_i = 1, \quad \sum_{i=1}^{n} \beta_{iy} = 0, \quad \text{and} \quad \sum_{k=1}^{n} \beta_{ki} = 0,$$

is accomplished with a fixed effects regression. Following Cornwell, Schmidt, and Sickles (1990), we specify β_{jt} as:

$$(6)\quad \beta_{jt} = \Omega_{j1} + \Omega_2 t + \Omega_3 t^2.$$

In this regression, the intercept term is omitted and variables to capture the technical efficiencies of banks (bank-specific dummy variables, bank-specific dummy variables multiplied by time, and bank-specific dummy variables multiplied by time-squared) are included. The regression model (5) is estimated after equation (6) is substituted into (5) for β_{jt}.

Using estimates of Ω_{jI} (for $I = 1, 2, 3$), the predicted values for the β_{jt} in equation (6) are generated. Defining the minimum of the predicted values as the "minintercept," time-variant and bank-specific cost efficiencies are obtained by taking the exponential of the difference between the minintercept and the predicted values.

Upon obtaining estimates of the β_{jt}'s, define $\hat{\beta}_{0t} = \min_j\{\hat{\beta}_{jt}\}$ as the estimated intercept of the cost frontier in period t. The cost efficiency for bank j at time t (CE_{jt}) is obtained as follows:

$$(7)\quad CE_{jt} = e^{-\hat{u}_{jt}},$$

where $\hat{u}_{jt} = (\hat{\beta}_{jt} - \hat{\beta}_{0t})$, and $e^{-\hat{u}_{jt}}$ represents the overall cost efficiency for bank j at time t.

Approaches for Explaining Differences in Efficiency

The One-Step Approach

Following Battese and Coelli (1993), the cost frontier is specified as:

$$(8)\quad C^b = C^0 * e^{V+U},$$

where V represents the pure random error and U is the one-sided error that is assumed to have only positive values. The one-sided error term U is assumed to be a function of firm-specific characteristics:

$$(9)\quad U_{it} = \sum_{j=1}^{J} \delta_j S_{ijt} + w_{it},$$

where δ_j denotes coefficients to be estimated, S_{ijt} represents firm-specific characteristics, and w_{it} denotes random errors which are assumed to have a truncated normal distribution with zero mean and standard deviation σ^2. The point of truncation is given as

$$-\sum_{j=1}^{J} \delta_j S_{ijt}.$$

Thus, w_{it} is restricted to the values that are greater than the truncation point, i.e.,

$$(10)\quad w_{it} \geq -\sum_{j=1}^{J} \delta_j S_{ijt}.$$

The detailed derivation of the log-likelihood function for the compound error term $U + V$ and the first derivatives of the log-likelihood function with respect to parameters are presented in Battese and Coelli (1993). To obtain the log-likelihood

function for a cost frontier, we need to modify the second term of the numerator in μ^* since the derived log-likelihood function in Battese and Coelli is for a production frontier. All parameters can be estimated using the maximum-likelihood estimation (MLE) method.

The Two-Step Approach

Investigating the sources of differences in efficiency requires the overall cost efficiency, which involves a fixed-effects model using panel data to obtain time-variant cost-efficiency measures. The stochastic frontier approach is laid out conceptually in (2) and upon estimation in (5). An alternative is the cost DEA approach which creates technical efficiency (TE) scores for each decision-making unit (DMU) by solving a linear programming problem. In the distance function literature, it is well known that:

$$(11)\quad TE_O\ score = D_O(x, y)$$

and

$$(12)\quad TE_I\ score = \frac{1}{D_I(x, y)},$$

where $D_O(\cdot)$ and $D_I(\cdot)$ represent the output distance and the input distance functions, respectively. An input distance function is defined as the maximum amount by which the input vector can be contracted along a radial line without reducing the output level.[1] An output distance function is defined as the minimum amount into which the output can be divided to reach the maximum possible output level without increasing input use. If the production technology exhibits constant returns to scale, the following equality holds:

$$(13)\quad TE_I\ score = \frac{1}{D_I(y, x)} = D_O(x, y) = TE_O\ score.$$

In evaluating the efficiencies of I firms with N inputs and K outputs, the reciprocal of the input distance function and input-oriented constant returns to scale (CRTS) TE score for the ith DMU can be calculated by solving the following linear programming problem:

$$(14)\quad \left[D_I(y_i, x_i)\right]^{-1} = \min \theta^i$$
$$\text{s.t.: } \theta^i x_{in} \geq \sum_{i=1}^{I} \lambda_i x_{in} \quad \forall\, n = 1, \ldots, N,$$
$$\sum_{i=1}^{I} \lambda_i y_{ik} \geq y_{ik} \quad \forall\, k = 1, \ldots, K,$$
$$\lambda_i \geq 0.$$

The cost efficiency of the ith DMU is defined as:

$$(15)\quad \frac{CE_i^0}{CE_i^b} = \frac{\sum_{n=1}^{N} w_{in} x_{in}^*}{\sum_{n=1}^{N} w_{in} x_{in}},$$

where x_{in}^* is the cost-minimizing input use of the ith DMU, and CE_i^0 and CE_i^b represent the minimum cost and the observed cost, respectively, for the ith DMU. Cost-minimizing input use for the ith DMU for the case of CRTS is obtained by solving the following linear programming problem:

$$(16)\quad \min \sum_{n=1}^{N} w_{in} x_{in}^*$$
$$\text{s.t.: } x_{in}^* \geq \sum_{I=1}^{i} \lambda_I x_{in} \quad \forall\, n = 1, \ldots, N,$$
$$\sum_{I=1}^{i} \lambda_I y_{ik} \quad \forall\, k = 1, \ldots, K,$$
$$\lambda_i \geq 0 \quad \forall\, i = 1, \ldots, I,$$

where w_{in} is the price of the nth input for the ith DMU, and x_{in}^* is the cost-minimizing input use implied by the linear programming solution. The CRTS assumption is used to obtain DEA cost-efficiency scores for the sake of consistent

[1] Define production technology as $T = \{(x, y)$: *x can produce y*$\}$. The input and the output distance functions are defined as

$$D_I(y, x) = \sup\left\{\lambda : \left(\frac{x}{\lambda}, y\right) \in T\right\} \text{ and}$$

$$D_O(x, y) = \inf\left\{\theta : \left(x, \frac{y}{\theta}\right) \in T\right\}.$$

comparison between DEA efficiency scores and SFA efficiency measures.

Cost efficiencies obtained by both SFA and DEA are then regressed on bank-specific characteristics to extract factors that likely influence efficiency differences across banks. Pairwise correlation analyses between the cost efficiency and bank-specific characteristics are also estimated.[2]

Efficiency Changes and Bank-Specific Characteristics

We can categorize banks into several classes by examining trends in cost efficiencies. More specifically, trends in cost efficiencies are estimated using the following regression model:

$$(17)\ CE = \alpha_0 + \alpha_1 TIME + \alpha_2 TIME^2 + \alpha_3 TIME^3.$$

The banks can be categorized into several classes. Based on this categorization, we can implement a multinomial logit model to identify the determinants of class membership. The dependent variable (Y) of this model takes a value of $j - 1$ for a firm that belongs to the jth class. The efficiency class choice of a bank is modeled as:

$$(18)\ C(Alt_j) = \beta_j x + \varepsilon_j \quad \text{for } j = 0, 1, \ldots, J-1,$$

where J alternatives exist and ε_j's are assumed to be independently and identically Gumbel distributed, and bank-specific characteristics along with the intercept term comprise X.

The observed choice will be j if:

$$(19)\ C(Alt_j) > C(Alt_k) \quad \forall\, k \neq j.$$

The choice probability is defined as follows:

$$(20)\ \text{Prob}(j) = e^{\beta_j x} \Big/ \sum_{j=0}^{J-1} e^{\beta_j x^*}.$$

Using the multinomial logit model, we can examine whether an increase in a firm-specific characteristic will increase the probability with which the firm belongs to class j (for $j = 1, \ldots, J$).

Sample Data and Definitions of Variables

The Agricultural Banking Data Series

Quarterly Call Report data, provided by the Chicago Federal Reserve Bank, contain comprehensive operating cost data for all U.S. banks and are used in this analysis. The database covers the time period between the first quarter of 1976 and the fourth quarter of 2005. Information for approximately 10,000 financial institutions is available via the database. The exact number of financial institutions in a specific quarter varies.

For this study, an agricultural bank is defined using the Federal Deposit Insurance Corporation (FDIC) criterion—namely those financial institutions whose agricultural loan to total loan ratio is at least 25% and therefore represent a focused set of banks supporting agricultural activities.[3] The time period

[2] For the implementation of the one-step approach, FRONTIER4.1 software is utilized. Like DEAP2.1, the implementation of the maximum-likelihood estimation regression is straightforward.

[3] Various agencies such as the Federal Reserve System (FRS), Federal Deposit Insurance Corporation (FDIC), and American Bankers Association (ABA) use their own criteria to identify agricultural financial institutions. FRS defines an agricultural bank as a bank that has more than the average agricultural loan ratio. With the average agricultural loan ratio at approximately 10% and varying quarter by quarter, the FRS's criterion defines a heterogeneous set of agricultural banks. The FDIC regards any financial institution whose agricultural loan ratio is no less than 25% as an agricultural bank. The ABA uses two criteria to identify agricultural banks. The first is the absolute dollar volume of agricultural loans and the other is the agricultural loan ratio. ABA classifies any bank that has an agricultural loan ratio greater than 50% or provides more than $2.5 million to the agricultural sector as an agricultural bank. The first criterion for ABA may be too strict while the second criterion may be too loose. Applying the ABA's criteria, the financial institutions included in the sample would present very heterogeneous agricultural loan ratios.

covered in the sample is chosen to be long enough to examine the trend of bank-specific technical inefficiencies. For these reasons, we selected the time period between the first quarter of 1996 and the fourth quarter of 2005 to construct our sample data, resulting in 519 banks consistently satisfying the FDIC criterion during the entire sample period.

Definitions of Inputs, Output, Input Prices, and Cost

Following the value-added approach, a single output is defined as the sum of total loans and total deposits. The three inputs specified are (*a*) labor, (*b*) expenses for the premises and fixed assets, and (*c*) the sum of interest and other expenses. Labor input is defined as the total number of employees. Expenses for the premises and fixed assets include all non-interest expenses related to the use of premises, equipment, furniture, and fixtures. Other expenses involve interest paid on deposits and other non-interest operating expenses. Except for the labor input, no explicit input price information is available.

Following Ferrier and Lovell (1990), input prices for the second and the third inputs are obtained by dividing each input into total deposits. Total cost *TC* is defined as $TC = w_1 * x_1 + x_2 + x_3$,[4] where w_1 is the price of the *i*th input and x_i is the *i*th input.

Bank-Specific Characteristics

The bank-specific characteristics to explain efficiency differences are partitioned into five broad categories: (*a*) bank size, (*b*) organizational form and regulatory structure, (*c*) bank safety and soundness, (*d*) raw performance measures, and (*e*) other bank characteristics. Variables and definitions for the characteristics are presented in Table 1.

Results

Results from the Two-Step Approach Using SFA

The regression result of equation (5) is presented in Table 2. In the interest of conserving space, the estimations of Ω_{1t}, Ω_{2t}, and Ω_{3t} are not reported in the table. All parameter estimates except those for $\ln(w_2)$ are statistically significant at the 1% level.

Figure 1 presents the trend of aggregated average cost efficiency across time periods and banks. The average cost-efficiency measure for agricultural banks reveals an initial peak at time period 4, followed by a generally decreasing trend along with two rebounds. The second-step regression result is presented in the second column of Table 3. All coefficient estimates for explanatory variables (except for *CHAR*) are statistically significant at the 5% significance level. Accounting for other characteristics, older banks are more efficient than newer banks. Federal Reserve System members (*FR*) tend to be less efficient than nonmembers, which may imply that regulation has a deteriorating impact on the efficiency of regulated banks. The most likely explanation is through the implicit safety net provided for member banks. The negative coefficient estimate for *TOTA* implies that a larger bank is, on average, less efficient than a smaller bank.

As suggested by the negative coefficient estimates for *CAM* and *NONACR*, banks taking more aggressive management strategies are more efficient than banks seeking less aggressive management strategies. The positive coefficient estimate for *NPLR* also supports this conclusion. Banks holding more construction and land development loans or holding more real estate loans are more efficient than other banks, while banks

[4] In the process of creating inputs and input prices, banks having zero inputs for at least one of their inputs or having negative inputs for at least one of their inputs were removed from the sample. Thus, we have 519 sample banks and the total number of observations for the balanced panel is 20,760 (519 banks * 40 quarters).

Table 1. Definitions of Bank-Specific Characteristics

Category	Variable	Definition
1 Bank Size	*TOTA*	ln(total assets)
2 Organizational Form, Regulatory Structure	*CHAR*	Charter type dummy (=1 if federally chartered, 0 otherwise)
	FR	Federal Reserve System member dummy (=1 if member, 0 otherwise)
3 Bank Safety and Soundness	*CAM*	Total Equity Capital/Total Assets
	NONACR	Nonaccrual Loans/Total Loans
	NPLR	Nonperforming Loans/Total Loans
4 Raw Performance Measures	*ROA*	Net Income/Total Assets
	ROE	Net Income/Total Equity
	RCOE	Total Operating Cost/Total Assets
5 Other Bank Characteristics	*YEAR*	ln(the year opened)
	LCLDTL	Construction and Land Development Loans/Total Loans
	RETL	Real Estate Loans/Total Loans
	INTL	Loans to Individuals/Total Loans

Note: Nonperforming loans are loans that are either 90 days past due or no longer yielding interest.

Table 2. Cost Frontier Estimation Results

Variable	Estimate	Std. Error	*t*-Value	Pr > | *t* |
$\ln(y)$	0.564700	0.019626	28.77	0.0001
$\ln(w_1)$	0.610403	0.027754	21.99	< 0.0001
$\ln(w_2)$	-0.057050	0.028900	-1.97	0.0484
$\ln(w_3)$	0.446649	0.039800	11.22	< 0.0001
$\ln(w_1)^2$	0.079990	0.005538	14.44	< 0.0001
$\ln(w_2)^2$	0.089289	0.003028	29.49	< 0.0001
$\ln(w_3)^2$	0.201008	0.006908	29.10	< 0.0001
$\ln(w_1)\times\ln(w_2)$	0.015864	0.003255	4.87	< 0.0001
$\ln(w_1)\times\ln(w_3)$	-0.095850	0.005717	-16.77	< 0.0001
$\ln(w_2)\times\ln(w_3)$	-0.105150	0.003257	-32.29	< 0.0001
$\ln(y)^2$	0.090864	0.001705	53.29	< 0.0001
$\ln(w_1)\times\ln(y)$	-0.083750	0.001988	-42.13	< 0.0001
$\ln(w_2)\times\ln(y)$	0.027520	0.001798	15.31	< 0.0001
$\ln(w_3)\times\ln(y)$	0.056233	0.002199	25.57	< 0.0001

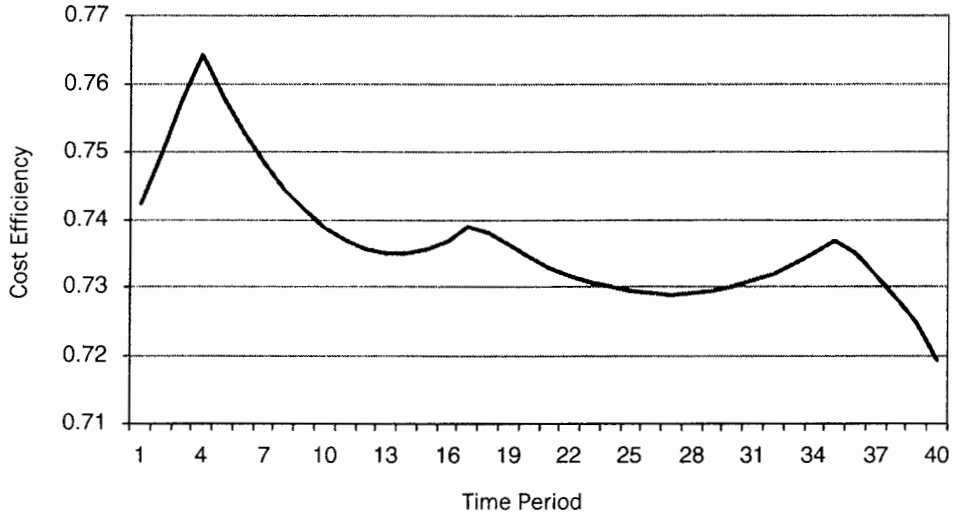

Figure 1. The Trend of Average Cost Efficiency for Agricultural Banks

Table 3. Regression of Cost Efficiency Measures on Bank-Specific Characteristics

Variable	Two-Step SFA	DEA	One-Step SFA with Sign Change
Intercept	0.136991	4.639441*	6.74801*
YEAR	0.134139*	-0.522400*	0.05872
CHAR	0.002094	-0.001230	0.00065
FR	-0.010300*	-0.014770*	-0.00390*
TOTA	-0.035050*	0.007311*	-0.90655*
CAM	-0.278390*	-0.250320*	0.47312*
NONACR	-0.247340*	-0.371330*	-0.11483*
NPLR	0.124754*	-0.009510	-0.02295
LCLDTL	0.076780*	-0.189000*	0.01440
RETL	0.031685*	-0.042020*	0.01487*
INTL	-0.426850*	-0.407750*	-0.13132*
ROA	3.371658*	6.313880*	-0.77571*
ROE	0.083050*	0.023067*	0.11598*
RCOE	-4.947970*	-11.046500*	-20.15910*
Adjusted R^2	0.229480	0.234070	—

Note: An asterisk (*) denotes statistical significance at the 5% level.

loaning more to individuals are less efficient than other banks. The positive signs of estimated coefficients for the raw profitability measures (*ROA* and *ROE*) imply that profitability is related positively to efficiency.

Results from the Two-Step Approach Using DEA

Table 4 shows average cost-efficiency scores obtained by DEA. For comparison, the average cost efficiency obtained from the two-step SFA is also represented in this table. The results are consistent with previous banking efficiency studies in which DEA yields a lower average efficiency measure than that of SFA. While the average values of SFA efficiency measures do not change much across time, those of DEA efficiency scores change considerably across time. This result seems reasonable since the frontier obtained by SFA is more restrictive than that obtained by DEA. While each slope parameter in SFA is assumed to have the same value across time, DEA does not impose any restriction on the form of the frontier.

The results from the regression of DEA cost-efficiency scores on bank-specific characteristics are presented in the third column of Table 3. Banks established earlier are less efficient than banks established later, and Federal Reserve System member banks are less efficient than other banks. The negative signs of coefficient estimates for *CAM* and *NPLR* are not consistent with each other. The signs of coefficient estimates for raw profitability measures (*ROA* and *ROE*) and the raw cost inefficiency measure (*RCOE*) are all consistent with a priori expectations.

One-Step Approach Results

The fourth column in Table 3 presents the sign changes of coefficient estimates for bank-specific characteristics obtained by applying the one-step approach to data. The signs of the estimated coefficients are changed for clearer interpretation because the coefficient estimates for bank-specific characteristics are obtained by specifying the one-sided error term U which depends on bank-specific characteristics, where the cost efficiency measure is defined as

Table 4. Comparison Between Average SFA Efficiency Measure and Average DEA Efficiency Score Across time Periods

Time Period	SFA	DEA
1	0.74222	0.62933
2	0.74999	0.45427
3	0.75747	0.64641
4	0.76401	0.68076
5	0.75807	0.67711
6	0.75284	0.71886
7	0.74830	0.66828
8	0.74444	0.23001
9	0.74125	0.67730
10	0.73871	0.67471
11	0.73682	0.40681
12	0.73557	0.50609
13	0.73495	0.63571
14	0.73497	0.63316
15	0.73563	0.64762
16	0.73691	0.68358
17	0.73883	0.69755
18	0.73801	0.70250
19	0.73608	0.40461
20	0.73438	0.51209
21	0.73291	0.63797
22	0.73167	0.64497
23	0.73067	0.64228
24	0.72989	0.38870
25	0.72933	0.67588
26	0.72901	0.61894
27	0.72892	0.64494
28	0.72906	0.65937
29	0.72943	0.61253
30	0.73004	0.62337
31	0.73089	0.63150
32	0.73198	0.40585
33	0.73331	0.56714
34	0.73489	0.57441
35	0.73672	0.60589
36	0.73501	0.60689
37	0.73157	0.56558
38	0.72811	0.56837
39	0.72464	0.57374
40	0.71924	0.62219
1–40	0.73667	0.59393

Table 5. Comparison of Average Values of Various Cost Efficiency Measures Across Time Periods

Time Period	Correlation Coefficient	Time Period	Correlation Coefficient
1	0.38780	22	0.46733
2	0.37800	23	0.46576
3	0.45704	24	0.36340
4	0.41393	25	0.40672
5	0.44371	26	0.42016
6	0.49918	27	0.39919
7	0.49642	28	0.35572
8	0.33482	29	0.35970
9	0.45323	30	0.38678
10	0.45416	31	0.36424
11	0.35840	32	0.29912
12	0.37531	33	0.37649
13	0.47037	34	0.40514
14	0.49520	35	0.39008
15	0.49530	36	0.38434
16	0.43483	37	0.40429
17	0.47902	38	0.41863
18	0.48750	39	0.42710
19	0.43575	40	0.40421
20	0.39528		
21	0.44425	1–40	0.28134

$CE = e^{U}$. Thus, a positive coefficient estimate for a bank-specific characteristic implies this characteristic is negatively related to its cost efficiency. The estimation results indicate that Federal Reserve System member banks are likely to be less efficient than other banks. The sign of the coefficient estimate for *TOTA* (with appropriate sign change) shows that larger banks tend to be less efficient. The sign of the coefficient estimate for *CAM* implies that banks pursuing a safety-first strategy are more likely to be efficient. However, the sign of the coefficient estimate for *NONACR* does not appear to support the sign of the coefficient estimate for *CAM*. Banks holding more real estate loans are more efficient than other banks while banks loaning more to individuals are less likely to be efficient. Finally, the signs of coefficient estimates for *ROA* and *ROE* are contradictory.

Comparison of Approaches

The estimated correlation coefficients between efficiency measures from two-step SFA and DEA efficiency scores are reported in Table 5. Two efficiency measures are related positively (but weakly) to each other for the entire panel, while the magnitudes of the correlation coefficients for each period change over time. Table 6 compares the average values of cost-efficiency measures obtained by the one-step approach with those obtained from two-step SFA and DEA approaches. Compared to the two-step SFA and DEA approaches, the one-step approach results in a smaller average CE.

Figure 2 presents trends of efficiency measures obtained by three approaches. While average efficiency measures obtained by the two-step SFA and one-step SFA vary little over time, the average efficiency measures obtained by DEA vary considerably across time. The observed variation in DEA efficiency scores implies that efficiency scores can be sensitive to stochastic shocks since DEA interprets stochastic shocks as contributions to inefficiency.

Simple regression analyses are implemented to examine whether the average efficiency measures obtained by various approaches present increasing or decreasing time trends. In each regression, the average efficiency is regressed on a time trend. Table 7 presents the results of these regression estimations. The two-step SFA presents a statistically significant negative coefficient estimate for the time trend, while coefficient estimates of time trend variables for the other two approaches are not statistically significant.

Comparison of Regression Results

Comparing the regression results from the SFA (Table 3) reveals that bank-specific characteristics result in a lower determination coefficient for the two-step SFA efficiency measures than for the DEA efficiency measures.

Table 6. Comparison of Cost-Efficiency Measures

Time Period	One-Step Approach	Two-Step SFA	DEA	Time Period	One-Step Approach	Two-Step SFA	DEA
1	0.11591	0.74222	0.62933	22	0.07084	0.73167	0.64497
2	0.08541	0.74999	0.45427	23	0.05230	0.73067	0.64228
3	0.06269	0.75747	0.64641	24	0.03838	0.72989	0.38870
4	0.04451	0.76401	0.68076	25	0.09824	0.72933	0.67588
5	0.11202	0.75807	0.67711	26	0.07652	0.72901	0.61894
6	0.08254	0.75284	0.71886	27	0.05982	0.72892	0.64494
7	0.06045	0.74830	0.66828	28	0.04538	0.72906	0.65937
8	0.04278	0.74444	0.23001	29	0.09776	0.72943	0.61253
9	0.10838	0.74125	0.67730	30	0.07835	0.73004	0.62337
10	0.07964	0.73871	0.67471	31	0.06312	0.73089	0.63150
11	0.05829	0.73682	0.40681	32	0.04954	0.73198	0.40585
12	0.04133	0.73557	0.50609	33	0.09658	0.73331	0.56714
13	0.10419	0.73495	0.63571	34	0.07933	0.73489	0.57441
14	0.07771	0.73497	0.63316	35	0.06490	0.73672	0.60589
15	0.05751	0.73563	0.64762	36	0.05059	0.73501	0.60689
16	0.04120	0.73691	0.68358	37	0.09491	0.73157	0.56558
17	0.10168	0.73883	0.69755	38	0.07670	0.72811	0.56837
18	0.07502	0.73801	0.70250	39	0.06115	0.72464	0.57374
19	0.05441	0.73608	0.40461	40	0.04667	0.71924	0.62219
20	0.03808	0.73438	0.51209				
21	0.09692	0.73291	0.63797	1–40	0.07104	0.73667	0.59393

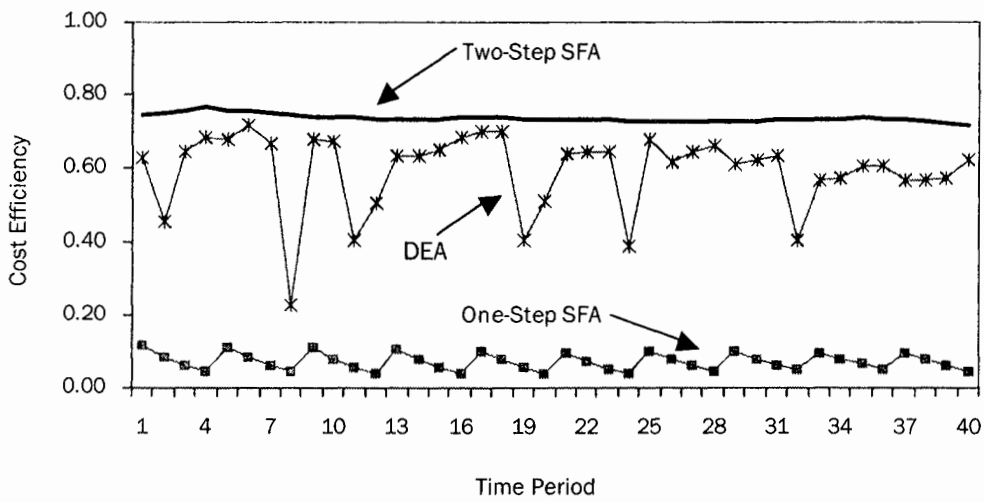

Figure 2. Comparison of Average Efficiency Measures from Two-Step SFA, DEA, and One-Step SFA

Table 7. Regression of Average Efficiency Measure on the Time Trend

Item	Two-Step SFA	DEA	One-Step SFA
Intercept	0.749721*	0.602910*	0.077209*
Time Trend	-0.000640*	-0.000044	-0.000300
Adjusted R^2	0.622610	-0.023890	-0.001780

Note: An asterisk (*) denotes statistical significance at the 5% level.

Table 8. Regression of One-Step Cost Efficiency on Bank-Specific Characteristics

Variable	Coefficient Estimate
Intercept	1.073130*
YEAR	-0.046780*
CHAR	-0.004540*
FR	-0.002550*
TOTA	-0.062560*
CAM	0.372839*
NONACR	0.108712*
NPLR	-0.142900*
LCLDTL	0.046242*
RETL	0.005361*
INTL	0.102088*
ROA	-1.121210*
ROE	0.097928*
RCOE	-1.044850*
Adjusted R^2 = 0.73	

We implement a regression of the CE from the one-step approach on bank-specific characteristics to compare the one-step approach results with those of the two-step approach to provide a common benchmark for comparison. The regression results are reported in Table 8. The high coefficient of determination seems to be built into the one-step approach, where the dependent variable is obtained by inverting the resulting value after taking the exponential of the predicted CE value generated by the one-step approach.

The inconsistency issue concerning the two-step approach estimators mentioned by Battese and Coelli (1993) is examined by comparing signs of coefficient estimates for the bank-specific characteristics in the one-step approach to those obtained by running a regression of the one-step CE on bank-specific characteristics. Notice that the dependent variable of the two-step approach is *cost efficiency*, while that of the one-step approach is the natural logarithm of *cost inefficiency*. Thus, a positive coefficient for a bank-specific characteristic implies that an increase in the characteristic results in efficiency enhancement (deterioration) for the two-step approach (for the one-step approach).

To obviate this confusion possibility, we changed the signs of coefficient estimates from the one-step approach. Table 9 presents the signs of coefficient pairs for each bank-specific characteristic with appropriate sign changes of one-step approach coefficient estimates. The table shows that the two regression results are not consistent with each other for four (of 13) bank-specific characteristics (*YEAR*, *CHAR*, *NONACR*, *INTL*), and only two bank-specific characteristics (*NONACR*, *INTL*) present statistically significant coefficient estimates for both approaches. The coefficient estimates of two raw profitability variables (*ROA* and *ROE*) for both approaches present the same signs, suggesting that the inconsistency issue for two-step approach estimates is not serious in this case.

Battese and Coelli (1993) demonstrate that biases of the two-step approach estimates will become larger when explanatory variables used to obtain a frontier (input prices and outputs for a cost frontier, inputs for a production frontier) are included as regressors in the second-step regression. However, two-step approaches can employ the instrumental variable estimation method to side-step this issue. We compare the second-step regression result of the two-step SFA approach with the one-step regression result in Table 10 to examine this issue further.

Table 9. Comparison of Signs of Coefficient Pairs for Each Bank-Specific Characteristic

Variable	One-Step Approach Regression w/ Sign Change	Regression of One-Step CE on Bank-Specific Characteristics
YEAR	+	– *
CHAR	+	– *
FR	– *	– *
TOTA	– *	– *
CAM	+ *	+ *
NONACR	– *	+ *
NPLR	– *	– *
LCLDTL	+	+ *
RETL	+ *	+ *
INTL	– *	+ *
ROA	– *	– *
ROE	+ *	+ *
RCOE	– *	– *

Note: An asterisk (*) denotes statistical significance at the 5% level.

Table 10. Comparison of One- and Two-Step Approaches

Variable	One-Step Approach Regression w/ Sign Change	Two-Step SFA Approach
YEAR	+	+ *
CHAR	+	+
FR	– *	– *
TOTA	– *	– *
CAM	+ *	– *
NONACR	– *	– *
NPLR	– *	+ *
LCLDTL	+	+ *
RETL	+ *	+ *
INTL	– *	– *
ROA	– *	+ *
ROE	+ *	+ *
RCOE	– *	– *

Note: An asterisk (*) denotes statistical significance at the 5% level.

As before, the signs of coefficient estimates obtained from the one-step approach are changed for the clear comparison and interpretation. In this table, the same signs of a pair of coefficients for each bank-specific characteristic imply that only three pairs of estimates—*CAM*, *NPLR*, and *ROA*—are not consistent with one another.

We expect the raw profitability measure *ROA* (the ratio of net income to the total equity) to be positively related with cost efficiency. The two-step approach result is consistent with this expectation while the one-step approach result is not. Greater profitability implying less cost efficiency seems questionable in a competitive operating environment. Considering the signs of coefficient estimates for *CAM* and *NPLR*, the two approaches imply polar opposite management strategies. The one-step approach suggests a "safety-first management strategy" whereas the two-step approach recommends an "aggressive management strategy."

Impacts of Bank-Specific Characteristics on Efficiency Changes

We implement the regression of cost efficiencies on the intercept term, time, and time-squared variables. Based on the signs and statistical significances of estimated coefficients, we classify sample agricultural banks into one of 10 categories. Table 11 presents the classifications and the numbers of agricultural banks belonging to each category. Table 12 provides a reclassification of these time profiles into six broad classes. Only 2% of the banks are chronically inefficient (CAT1), and a neglible number of banks are always efficient (CAT2). Most of the banks present a trajectory that is classified as performing temporarily well (CAT5 at 33.5%), or poorly (CAT6 at 51.4%). Relatively few banks can be viewed as improving (CAT4).

Table 11. Types of Cost Efficiency Changes for Agricultural Banks

Category	Condition	No. of Banks
1	$\alpha_0 > 0,\ \alpha_1 > 0,\ \alpha_2 = 0$	17
2	$\alpha_0 > 0,\ \alpha_1 < 0,\ \alpha_2 = 0$	30
3	$\alpha_0 > 0,\ \alpha_1 > 0,\ \alpha_2 < 0$	127 (120)[a]
4	$\alpha_0 > 0,\ \alpha_1 < 0,\ \alpha_2 < 0$	26
5	$\alpha_0 > 0,\ \alpha_1 > 0,\ \alpha_2 > 0$	12
6	$\alpha_0 > 0,\ \alpha_1 < 0,\ \alpha_2 > 0$	257 (245)[a]
7	$\alpha_0 \geq 0.8,\ \alpha_1 = 0,\ \alpha_2 = 0$	2
8	$\alpha_0 < 0.8,\ \alpha_1 = 0,\ \alpha_2 = 0$	8
9	$\alpha_0 > 0,\ \alpha_1 = 0,\ \alpha_2 < 0$	23
10	$\alpha_0 > 0,\ \alpha_1 = 0,\ \alpha_2 > 0$	17

Notes: The regression equation is $CE = \alpha_0 + \alpha_1 TIME + \alpha_2 TIME^2$, where *CE* is cost efficiency; 19 banks were fit into cubic forms, $\alpha_0 + \alpha_1 TIME + \alpha_2 TIME^2 + \alpha_3 TIME^3$.

[a] Values in parentheses show the numbers of banks excluding banks that are fit into cubic forms.

Table 12. Reclassification of Types of Cost Efficiency Changes

Class	Definition and Included Types	No. of Agricultural Banks Included
CAT1	Chronically Inefficient (Category 8)	10
CAT2	Chronically Efficient (Category 7)	2
CAT3	Increasingly Inefficient (Category 2)	35
CAT4	Increasingly Efficient (Categories 1 and 5)	31
CAT5	Temporarily Efficient (Categories 3, 4, and 9)	174
CAT6	Temporarily Inefficient (Categories 6 and 10)	267
	Total:	519

Notes: We reclassified 19 banks which were fit into cubic forms, $\alpha_0 + \alpha_1 TIME + \alpha_2 TIME^2 + \alpha_3 TIME^3$, according to their cost efficiency trend graphs.

A multinomial logit analysis is employed to examine the impacts of bank-specific characteristics on the types of CE profile changes over time.[5] The marginal effects of the bank-specific characteristics on the probabilities are presented in Table 13, which can offer a more interpretive perspective for future policy measures to enhance overall agricultural banking efficiencies. As indicated by these results, some variables, such as *INTL*, have a clear impact alone on the efficiency classification of a bank where increases in this factor lead to a higher probability of the bank being a member of an inefficient category, and a decrease in this factor will lower the probability the bank is a member of an efficient category. Increases in *TOTA* are associated with an increase in the probability of membership in the chronically inefficient or increasingly inefficient class (CAT3), as well as a decrease in the increasingly efficient class (CAT4).

[5] With nearly 80% of the estimated coefficients significant at the 0.05 level, the overall estimation presents a χ^2 value significant at the 0.001 level. Estimation results are available from the authors upon request.

Table 13. Marginal Effects of Bank-Specific Characteristics on the Probabilities

Explanatory Variables	CAT 1	CAT 2	CAT 3	CAT 4	CAT 5	CAT 6
Constant	1.4935***	0.0095*	2.8784***	0.5447	-8.1105***	3.1845
YEAR	-0.2189***	-0.0013*	-0.4207***	-0.0603	1.0256***	-0.3245
TOTA	0.0095***	0.0000	0.0228***	-0.0161***	0.0419***	-0.0581***
CAM	0.0843***	-0.0004	-0.0106	0.3282***	0.0039	-0.4052***
NONACR	0.0552	0.0032*	0.0701	-0.4815**	0.9506**	-0.5977
NPLR	0.0291	-0.0031*	0.5229***	0.0402	-0.0663	-0.5228
LCLDTL	0.1031*	-0.0002	0.1314	-0.4504***	1.4889***	-1.2728***
RETL	0.0180*	0.0001*	-0.1906***	-0.0148	0.0750**	0.2623***
INTL	0.1043**	-0.0018*	0.0508*	-0.5213***	-0.8430***	1.2111***
ROA	-0.1098	-0.0027*	-2.8935***	-0.6025**	-1.3622	4.9706***
ROE	-0.0502***	0.0000	-0.0291	0.0371**	0.1247***	-0.0826*
RCOE	0.6030***	0.0030*	4.2717***	0.3307	0.5033	-5.7116**

Notes: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively. The LIMDEP program was used for the results reported in this table.

Other variables indicate conflicting impacts; for example, an increase in *ROA* can increase the probability of being in the increasingly inefficient (CAT3) and increasingly efficient (CAT4) classes.

Concluding Comments and Implications

U.S. agricultural production has never been more capital intensive. Therefore, measuring and evaluating the efficiency of agricultural financial institutions is important for better understanding the extent to which credit and financial services are being efficiently delivered to the agricultural sector. Different methodological approaches are implemented and compared in an effort to examine the relationship between efficiency measures and bank-specific characteristics.

For the one-step approach, we used the cost frontier specification developed by Battese and Coelli (1993). The regression of one-step CE measures on bank-specific characteristics reveals that the inconsistency issue is not serious in examining whether the second-step regression results in inconsistent estimates.

For the two-step approaches, two sets of cost-efficiency measures of agricultural banks are obtained: one by stochastic frontier analysis (SFA) and the other by data envelopment analysis (DEA). These efficiency scores are then regressed on bank-specific characteristics to determine the extent to which the characteristics can explain bank efficiency. The regression results reveal that bank-specific characteristics explain DEA efficiency scores better than SFA efficiency measures; the coefficient of determination is higher in the case of DEA than SFA. On the other hand, the signs of some coefficient estimates, such as those for a bank's equity-to-asset ratio and ratio of nonperforming loans to total loans, do not have the appropriate anticipated sign in the DEA regressions.

The empirical evidence also suggests that older, smaller banks tend to be more efficient than their newer, larger counterparts. Profitability is also consistent with efficiency in this context. Perhaps not surprisingly, our analysis finds Federal Reserve System member banks tend to be less efficient than nonmember banks. It is possible that more intense banking regulation and the implicit safety net afforded member banks

undermine the efficiency with which these banks operate to some degree. These results may have implications for banking regulators seeking to ensure the safety and soundness of the banking sector. Efforts to control undue risk taking by banks through regulations regarding capital ratios, for example, may have the undesirable effect of undermining the efficiency with which credit is delivered to the agricultural sector. Such inefficiencies could result in increased credit costs for farmer borrowers.

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Estimating Delinquency Migration and the Probability of Default from Aggregate Data

Jeffrey R. Stokes and Brent A. Gloy

Abstract

Defaulting on a mortgage represents the ultimate consequence of past decisions to delay payment. While many modeling approaches are available to estimate the probability of default, most if not all require account-level data. Further, past research has not attempted to estimate the probability that a current loan will transition among delinquency states prior to default. In this paper, we present an econometric approach that makes use of publicly available aggregate data for estimating the probability of delinquency and the probability of default. The results suggest the approach may have merit for monitoring bank performance as well as usefulness for banks' risk management efforts.

Key words: delinquency, Markov chain, maximum entropy, probability of default

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Default and prepayment risk are a central concern for financial institutions for a variety of reasons including performance measurement, risk management, and regulatory compliance. These two risks have received considerable attention in the literature. For example, with respect to agricultural mortgages, Katchova and Barry (2005), Novak and LaDue (1994, 1997), and Sherrick, Barry, and Ellinger (2000), all concentrate on credit (i.e., default) risk, and Chhikara and Hanson (1993), Brinch and Stokes (2001), and Stokes and Brinch (2001) focus on prepayment risk in addition to credit risk.

While these studies and others like them are important for understanding credit and prepayment risk, the literature has much less to say about the estimation of the risk associated with mortgage delinquency. Although mortgage delinquency is not a sufficient condition to ensure default, it is a necessary condition for default, as loans will generally progress through various stages or states of delinquency prior to an ultimate default. In addition, there is a direct linkage between delinquency and credit and prepayment risk. Delinquent loans are more likely to default, while current (i.e., nondelinquent) loans are more likely to remain current or prepay.

In one of the first studies of mortgage delinquency, Green and von Furstenberg (1975) attribute the paucity of research on delinquency to a lack of relevant data appropriate to analyze the occurrence. Only a few other studies (such as Morton, 1975; Campbell and Dietrich, 1983; Teo, 2004; and Diaz-Serrano, 2005) examine delinquency risk specifically. Campbell

and Dietrich (1983) approach the issue of delinquency from the perspective of a utility-maximizing borrower operating in a dynamic choice environment. At each point in time of the life of a mortgage, borrowers observe a set of state variables and choose one of four utility-maximizing actions: default, delay payment, prepayment, or continue to service the mortgage. Similarly, in their review of the mortgage literature, Quercia and Stegman (1992) describe typical borrower repayment models as depicting borrowers dynamically selecting one of these optimal actions to maximize their utility.

In reality, default may not be a decision at all, but rather the ultimate consequence of previous decisions to delay payment (i.e., delinquency) and subsequent failure to bring the loan back to current status by making up the payments. In other words, there may be something to gain by estimating the probability that loans transition among delinquency states.

One obvious drawback to estimating the probability of default and potentially the probability of delinquency using current methods is the need for micro-level data—that is, loan- or account-level data where the status (i.e., current, past-due, default, etc.) of the loan can be observed at discrete points in time. Unlike Gloy, LaDue, and Gunderson (2005), and Zech and Pederson (2004), applied researchers rarely have access to such micro-level data. This typically means that two choices are available to the applied researcher: namely, to not attempt any estimation at all, or to seek out a modeling approach that might be sensitive to available data.

Given the lack of research on mortgage delinquency in general and for agricultural loans specifically, we take the latter approach and model mortgage delinquency as a Markov chain using publicly available data. In our model, a loan can remain current, transition among various states of delinquency, or charge off (default) from period to period. The dollar volume of loans in each state of the chain is observable, but the transition of accounts among states of the Markov chain over time is not. Faced with this ill-posed problem, we use an entropy-based econometric technique to elicit the probability distribution of the transition probabilities.

Through our demonstration of the entropy approach, our contribution is to add to the number of ways to estimate the probability of default and also to the number of ways to estimate credit ratings migration since our approach can be applied in this setting as well. Last, the Markov chain framework for loan delinquency necessitates consideration of how to handle the bank's changing loan volume over time. When using the Markov model, it is typical to specify an ad hoc pool size from which the proportion of the observations in each state including the pool can be determined. These data are then used to estimate the transition probabilities. We take a more innovative approach and specify a model where the size of the bank's loan pool is estimated simultaneously with the transition probabilities. This pool size estimate gives an indication of how much loan volume is both realized and unrealized by the bank and is therefore also useful for bank performance measurement and risk management.

Delinquency Dynamics

Whenever a stochastic process can frequent only one of a finite number of potential states at discrete points in time, the discrete time Markov chain model is a potentially appropriate description of the stochastic process. More formally, a Markov process $\{X_t\}$ is a stochastic process with the property that, given the value of X_t, the values of X_s for $s > t$ are not influenced by the values of X_u for $u < t$ (Taylor and Karlin, 1994). This leads to the Markov property

$$\Pr\{X_{n+1} = j \mid X_0 = i_0, \ldots, X_{n-1} = i_{n-1}, X_n = i\}$$
$$= \Pr\{X_{n+1} = j \mid X_n = i\} = p_{ij},$$

for all time points n and all states $i_0, \ldots, i_{n-1}, i, j$.

Since bank loans can be classified according to delinquency status at discrete points in time, the Markov chain model is one way to characterize the dynamics of bank loan delinquency. For example, the finite state space is comprised of a current state which shows how much of the bank's portfolio is made up of loans that are being paid back on schedule, various delinquency states which show how much of the bank's portfolio is past due and by how many days, and default which shows how much of the bank's portfolio charged off over the discrete time step between observations of the data.

The p_{ij} of the Markov chain are then the (stationary) probability of loans in one state transitioning to any of the other states over a discrete period of time. All Federal Deposit Insurance Corporation (FDIC) insured financial institutions report on the dollar value of loans that are current, 30–89 days past due, greater than 90 days past due, nonaccruing, and charged off during a quarter. Arranged into a matrix, **P**, defined by these states, a quarterly transition probability matrix can be represented as:

(1) $\mathbf{P} =$

$$\begin{bmatrix} p_{cu,cu} & p_{cu,30} & p_{cu,90} & p_{cu,na} & p_{cu,df} & p_{cu,ex} \\ p_{30,cu} & p_{30,30} & p_{30,90} & p_{30,na} & p_{30,df} & p_{30,ex} \\ p_{90,cu} & p_{90,30} & p_{90,90} & p_{90,na} & p_{90,df} & p_{90,ex} \\ p_{na,cu} & p_{na,30} & p_{na,90} & p_{na,na} & p_{na,df} & p_{na,ex} \\ p_{df,cu} & p_{df,30} & p_{df,90} & p_{df,na} & p_{df,df} & p_{df,ex} \\ p_{en,cu} & p_{en,30} & p_{en,90} & p_{en,na} & p_{en,df} & p_{en,ex} \end{bmatrix},$$

where the subscripts are defined as follows: *cu* (current), 30 (30–89 days past due), 90 (greater than 90 days past due), *na* (nonaccruing), *df* (default), *en* (entry), and *ex* (exit). Assuming quarterly data, one quarter is represented on the left side of the matrix with a subsequent quarter on the upper portion of the matrix whereby, for example, $p_{cu,cu}$ represents the probability of a current loan remaining current one quarter later. The entry and exit states are required to allow new loans to enter the bank's balance sheet and existing loans to exit via prepayment or maturity. In addition, some of the probabilities appearing in (1) must be restricted in value. These ideas are developed more fully later in the paper.

Estimating the probabilities in (1) is a complicated task for a variety of reasons. First, micro-level data documenting state transitions would typically be required for the estimation of the transition probabilities. Lee, Judge, and Takayama (1965) have shown that maximum-likelihood estimates of stationary transition probabilities are relatively easy to obtain when micro-level data are available. If micro-level data are unavailable or if the Markov chain is not stationary, estimation can be much more difficult. In the stationary case when micro-level data are unavailable, proportional data have been shown to be useful for the estimation of transition probabilities (Lee, Judge, and Zellner, 1970). However, it is often the case that the Markov chain problem is ill-posed since a short time series of data can easily cause the number of unknown parameters in the model to exceed the number of data points (Golan, Judge, and Miller, 1996), making the model underdetermined. This is easily the case in the context of estimating transition probabilities for the matrix in (1). With six states, 25 parameters (transition probabilities) would need to be estimated for a stationary Markov chain.[1]

Further complicating the estimation are the entry and exit states which allow new loans to enter and prepays or mature loans to exit the bank's portfolio. When using the Markov chain model, a pool state is often specified to allow for such entry and exit. However, when using proportional data, the size of the pool is

[1] A 6 x 6 square matrix has 36 probabilities. However, the probabilities in each row must sum to one and the default state is an absorbing state leaving at least 25 unique probabilities to be estimated. Other restrictions may further reduce the number of parameters to be estimated.

unknown and has implications for the estimation of the transition probabilities (Stanton and Kettunen, 1967). The next section describes the data and modeling approach used in this study and the unique way in which pool size is accommodated.

Empirical Model

Following the early work of Shannon (1948), Golan, Judge, and Miller (1996) propose a system for estimating the transition probabilities of a Markov chain based on maximizing the Shannon entropy function. In the simplest case, the Markov problem is cast as a pure inverse problem:

$$
\begin{aligned}
(2)\quad & \max -\sum_i \sum_j p_{ij} \ln(p_{ij}) \\
& \text{s.t.: } y_j(t+1) = \sum_i y_i(t) p_{ij} \quad \forall\, t, j, \\
& \sum_j p_{ij} = 1 \quad \forall\, i, \\
& 0 \le p_{ij} \le 1 \quad \forall\, i, j.
\end{aligned}
$$

In (2), the p_{ij} represent the stationary probability of transitioning from state i to state j over one time period. The objective function measures the Shannon entropy function which takes a maximum when the distribution of transition probabilities is uniform. The first set of constraints represents the Markov condition for proportional time-dated data $y_i(t)$ and $y_j(t+1)$,[2] and the second set of constraints are the row sum conditions associated with the Markov chain. The last set of constraints ensures the estimated probabilities are proper probabilities.

The concept of entropy in this context is relatively simple. Specifically, we seek to model all that is known and assume nothing about what is unknown. In other words, given a collection of data (information), choose a model which is consistent with all the facts, but which is otherwise as uniform as possible. The entropy of the distribution of transition probabilities is maximized in an effort to reduce information uncertainty.

The system presented in (2) is a pure inverse problem and is only appropriate if the data-generating process is Markov and, further, the data are observed without error. While the former assumption for delinquency is realistic at least as a working assumption, the latter is unrealistic. Point estimates like those resulting from a system such as (2) are likely less appealing than a range of probabilities from which estimation precision can be determined. Additionally, non-sample information may be available and desirable to incorporate into the estimation.

Golan, Judge, and Miller (1996) suggest using a specification such as that presented in (3) subject to (4), where the system (2) has been augmented to accommodate these deficiencies. The minimum cross-entropy formalism of the stationary Markov problem is constructed as:

$$
\begin{aligned}
(3)\quad \min_{\pi_{ijm},\, \omega_{ijm}} \Psi(\boldsymbol{\pi}, \boldsymbol{\omega}) = & \sum_i \sum_j \sum_m \pi_{ijm} \ln\left(\frac{\pi_{ijm}}{\tilde{\pi}_{ijm}}\right) \\
& + \sum_i \sum_j \sum_m \omega_{ijm} \ln\left(\frac{\omega_{ijm}}{\tilde{\omega}_{ijm}}\right)
\end{aligned}
$$

subject to:

$$
\begin{aligned}
(4)\quad & y_j(t+1) - \sum_i y_i(t) \sum_m z_m \pi_{ijm} \\
& \quad + \sum_m v_m \omega_{ijm} = 0 \quad \forall\, t, j, \\
& 1 - \sum_j \sum_m z_m \pi_{ijm} = 0 \quad \forall\, i, \\
& 1 - \sum_m \pi_{ijm} = 0 \quad \forall\, i, j, \\
& 1 - \sum_m \omega_{ijm} = 0 \quad \forall\, t, j, \\
& 0 \ge \pi_{ijm}, \omega_{ijm} \le 1.
\end{aligned}
$$

In (3) subject to (4), the sum product of a discrete distribution of estimated transition probabilities, π_{ijm}, and a parameter support vector, $\mathbf{z}$, determine the desired transition probabilities, p_{ij}, i.e.,

[2] Proportional data are assumed since they are all that is publicly available. Lee, Judge, and Zellner (1970) show how proportional data can be modeled as a Markov chain.

$$p_{ij} = \sum_m z_m \pi_{ijm}.$$

Additionally, the specification allows for the possibility that there is error in the Markov relation in (4) by including an error term expressed as the sum product of an error support vector, **v**, and errors, ω_{ijm}, i.e.,

$$\varepsilon_{ij} = \sum_m v_m \omega_{ijm}.$$

The remaining equations ensure that the estimated probabilities are proper probabilities. Non-sample information is introduced through the prior probability distributions for the probabilities and errors and are expressed in the objective function as $\tilde{\pi}_{ijm}$ and $\tilde{\omega}_{ijm}$. Unless prior distributions are explicitly specified, a uniform prior is implicitly assumed by the specification in (3).

Data

To estimate the transition probabilities, a time series of actual bank data showing the proportion of agricultural loans in various delinquency categories is required. This study utilizes quarterly observations on the dollar value of agricultural real estate loans in current, past due 30–89 days, past due more than 90 days, nonaccrual, and charge-off states. The data were collected for Pinnacle Bank in Pappilion, Nebraska, which until the most recent quarter was the largest agricultural bank by loan volume.

Data at this level of detail are available for 18 quarters beginning in March 2001 and ending June 2005. Before March of 2001, banks reported the amount of loans in the past-due more than 90 days, nonaccrual, and charge-off states, but the current and 30–89 days past-due states were combined for confidentiality purposes. The relatively short time period (4½ years) makes a stationary modeling approach justifiable at least as an initial modeling. In addition, the short time series make the entropy approach imperative since there are more parameters to estimate than data points, as discussed below.

The FDIC data were used to construct shares of agricultural real estate loans in each state for each quarter. In the process of creating the shares, it is necessary to modify the charge-off data because charge-off is an absorbing state. When viewed as an absorbing state, reported charge-off data are flow data, whereas the amount of loans in the other states are stocks. Therefore, for consistency with the other data in the model, the charge-off data must be converted to a stock. This was accomplished by accumulating the dollar value of loans flowing into the charge-off state over the sample period. While this adjustment is necessary for the estimation of transition probabilities for states communicating with charge-off, transition probabilities from the charge-off state to other states are necessarily zero. In other words, once a loan enters the charge-off state it cannot leave that state.

New loan volume and loan volume that leaves the bank's portfolio through means other than default (either prepayment or through maturity) must be accounted for as well, since failure to do so would result in the implicit assumption that loan volume expansion and contraction occurs proportionally to the states modeled.[3] However, from quarter to quarter, the data available only show the net change (increase or decrease) in the size of the bank's agricultural loan portfolio.

Given this aggregated feature of the data, an additional state representing a pool of new and retired loan volume is necessary. Any new loans come into the system from the pool and any repaid loans transition from the bank's balance sheet to the pool. The difficulty here is that the size of the pool represents the magnitude of Pinnacle's realized and unrealized loan volume, an unknown dollar value that affects the magnitude of the remaining shares. The minimum size of the pool can

[3] For example, by not allowing entry and exit, a 10% contraction in overall loan volume from one quarter to the next would presuppose an unrealistic 10% contraction in current loan volume, a 10% contraction in 30–89 days past-due loan volume, etc.

be inferred directly from the data as the maximum loan volume actually experienced by the bank over the sample period. The bank's portfolio expands over a quarter whenever loan volume increases. This expansion causes the pool of loan volume to shrink, as was typically the case for Pinnacle Bank over the sample period. The transition probabilities associated with the pool indicate the likelihood that loans in the bank's portfolio transition to the pool (exit) by means other than default, or enter the bank's portfolio from the pool.

While knowing the minimum pool size is useful information, imposing it on the share data is ad hoc because the pool represents an unknown loan volume which may be considerably larger than minimum observed loan volume depending on the bank's operating and competitive situation. More importantly, Stanton and Kettunen (1967) have shown that the number of potential entrants to a Markov chain system affect the estimation of all the transition probabilities and the equilibrium distribution of the system. Consequently, a significant extension of the Markov model is the simultaneous estimation of the size of the bank's loan pool and the transition probabilities. Such an approach thereby negates the need for an assumed pool size as in all previous structural change studies making use of the Markov model. Additionally, the estimate provides a bank with information about the size of its loan pool which can be compared to its realized or observed loan volume to gauge the extent to which resources are being allocated properly to enhance competitiveness.

As noted above, the difficulty in adding this feature to the model is that the magnitude of the bank's loan pool directly affects the share data, $y_i(t)$ from which estimates of the transition probabilities originate. Let $i = N$ represent the pool state and $Y_i(t)$ represent dollars of loan volume in state i at time t. Let $\gamma(t)$ represent total loan volume in states other than N so that

$$(5) \quad \gamma(t) = \sum_{i \neq N} Y_i(t) \quad \forall\, t.$$

Next, let $\eta(t)$ represent the net change in loan volume from one quarter to the next whereby

$$(6) \quad \eta(t) = \gamma(t+1) - \gamma(t) \quad \forall\, t < T$$
$$\text{and} \quad -\infty \leq \eta(t) \leq \infty.$$

Letting $\mathbf{d}$ be a parameter support vector for the unknown loan volumes, the magnitude of the pool at time $t = 1$ can be determined using (5) so that

$$(7) \quad Y_N(t) = \sum_m \beta_m d_m - \gamma(t),$$

while for $t > 1$ we have

$$(8) \quad Y_N(t) = Y_N(t-1) - \eta(t),$$

where β_m are probabilities associated with each parameter support value with

$$\sum_m \beta_m = 1.$$

To complete the estimation, let $\tau(t)$ represent the sum of observed and unobserved loan volume so that

$$(9) \quad \tau(t) = \gamma(t) + Y_N(t) \quad \forall\, t.$$

The proportion of loans in each state required by the Markov relation in (4) are then determined as

$$(10) \quad y_i(t) = \frac{Y_i(t)}{\tau(t)} \quad \forall\, t, i.$$

Augmenting the objective function in (3) to formalize the cross-entropy estimation of transition probabilities and loan volume results in the new objective function:

$$(11) \quad \boldsymbol{\Psi}(\boldsymbol{\pi}, \boldsymbol{\omega}, \boldsymbol{\beta}) = \sum_i \sum_j \sum_m \pi_{ijm} \ln\left(\frac{\pi_{ijm}}{\tilde{\pi}_{ijm}}\right) + \sum_i \sum_j \sum_m \omega_{ijm} \ln\left(\frac{\omega_{ijm}}{\tilde{\omega}_{ijm}}\right) + \sum_m \beta_m \ln\left(\frac{\beta_m}{\tilde{\beta}_m}\right),$$

with the new third term in (11) reflecting the uncertainty in the size of the loan pool

facing the bank. In (11), $\tilde{\boldsymbol{\beta}}$ is a vector of prior probabilities for loan volume. Notice that the model chooses probabilities for each loan support value. The sum product of these probabilities and support values is then used via equation (7) to determine the proportion of loan volume in each of the remaining states. This feature of the model is perhaps the most compelling reason for the entropy specification in that the number of unknowns far exceeds the number of data points. Equation (11) is minimized subject to the constraints in (4)–(10).

Finally, transition probabilities from the pool to certain states must be restricted to zero when using quarterly data. For example, it is impossible for a loan originated in one quarter to transition to the nonaccrual state one quarter later. Therefore, the transition probabilities from the pool and current states to the three states of (*a*) greater than 90 days past due, (*b*) nonaccrual, and (*c*) charge-off are restricted to zero. Also restricted to zero are transition probabilities for movement from the 30–89 days past-due (more than 90 days past-due) state to the nonaccrual and charge-off (charge-off) states. Last, transitioning from the nonaccrual state back to the 30–89 days past-due and more than 90 days past-due states in one quarter is also precluded.

Since the transition probabilities are bounded between zero and one, a logical choice for the probability parameter support vector would be discrete points in the unit interval, such as $\mathbf{z}$ = [0 ¼ ½ ¾ 1]. Similarly, the error support vector is specified as $\mathbf{v}$ = [-1 -½ 0 ½ 1] which imposes a symmetric error distribution with values consistent with the magnitude of error possible given the size of the probabilities to be estimated. That is, the most we can misestimate a transition probability is by a magnitude of one and the error support chosen captures this possibility. Finally, the parameter support vector for potential loan demand is specified (in millions) as $\mathbf{d}$ = [$100 $150 $200 $250 $300].[4] Prior probabilities for the transition probabilities ($\tilde{\pi}_{ijm}$), errors ($\tilde{\varepsilon}_{ijm}$), and potential loan demand ($\tilde{\boldsymbol{\beta}}$) were all assumed to be uniform.

Results

With six states and five parameter supports for each state, it is not practical to present the results from the full estimation. In addition, transition probabilities are probably best thought of in an annual context and the estimation, having used quarterly data, results in quarterly transition probabilities. To circumvent these issues, presented in Table 1 is a matrix of annualized stationary transition probabilities for Pinnacle's loan portfolio. These probabilities were determined by first estimating the π_{ijm} by minimizing (11) subject to (4)–(10), then recovering quarterly probabilities via

$$p_{ij} = \sum_m z_m \pi_{ijm},$$

and finally raising the resulting quarterly matrix to the 4th power to put the estimates in annual terms.

The resulting matrix contains annual estimates of the probability of loans in Pinnacle's portfolio transitioning to various stages of delinquency, default, and exit (prepayment or maturity) over the course of one year. For example, a loan that is current has about a 60.1% chance of remaining current next year, a 6.5% chance of becoming 30–89 days past due, a 2.0% chance of becoming more than 90 days past due, a negligible chance (due to rounding) of entering nonaccrual status, and a zero probability of defaulting. The data also suggest that a current loan has a 31.4% chance of either prepaying or maturing in the next year.

[4] Pinnacle's maximum loan volume over the sample period is suggestive of a minimum pool size of $151 million. The parameter support vector specified contains this value but allows for a larger loan volume if the data suggest this is the case.

Table 1. Annualized Estimates of Transition Probabilities and (Normalized Entropy Measures) for Pinnacle Bank

	Current	30–89 Days Past Due	90 or More Days Past Due	Non-accrual	Charge-Off (default)	Exit (prepayment or mature)
Current	60.08% (0.9894)	6.46% (0.0029)	2.03% (0.0000)	0.00% (0.0000)	0.00% (0.0000)	31.43% (0.9854)
30–89 Days Past Due	51.89% (0.8403)	9.71% (0.8057)	5.92% (0.8343)	3.39% (0.0000)	1.24% (0.0000)	27.86% (0.8574)
90 or More Days Past Due	49.65% (0.7601)	8.81% (0.7441)	4.80% (0.7550)	4.00% (0.7551)	7.20% (0.0000)	25.55% (0.7607)
Nonaccrual	39.90% (0.8413)	4.29% (0.0000)	1.16% (0.0000)	1.54% (0.8330)	32.55% (0.8328)	20.57% (0.8331)
Charge-Off (default)	0.00% (0.0000)	0.00% (0.0000)	0.00% (0.0000)	0.00% (0.0000)	100.00% (0.0000)	0.00% (0.0000)
Entry (new loan)	63.50% (0.7298)	9.43% (0.7298)	2.00% (0.0000)	0.93% (0.0000)	0.00% (0.0000)	24.14% (0.0000)

This result appears high but is not completely unanticipated, given the period of time covering the sample data was largely a time of falling interest rates in which many prepayments occurred.

The fact that the estimated probability of default for a current loan is zero is potentially problematic since no matter how high quality a loan is, there is always at least a small probability of default. However, the result is consistent with many past studies showing the same result for highly rated bonds. For the case of agricultural loans, estimates by Gloy, LaDue, and Gunderson (2005) and Behrens and Pederson (2005) indicate that the likelihood of a high quality credit, such as a current loan, transitioning to default is very nearly zero.

Below each transition probability estimate is a measure referred to as the normalized Shannon entropy measure. The statistic measures the information content in the estimates and is bounded by zero and one. Maximum entropy (or minimum cross-entropy) uncertainty is consistent with values for normalized entropy equal to one, while values closer to zero reflect less entropy uncertainty. The restrictions discussed above necessarily imply a zero value for the restricted parameters (e.g., the probability of transitioning from entry to past-due 90 or more days). However, most parameters have normalized entropy measures consistent with less information uncertainty. This is especially true for the probability of default from all states except nonaccrual. Obvious exceptions are current-to-current and current-to-exit transition probabilities. The overall system normalized entropy is 0.6893, which is reasonably consistent with less information uncertainty since it is fairly far from one.

Considering the remainder of the matrix, the probability of default rises as delinquency increases, and culminates in a 32.6% probability of default once a loan enters the nonaccrual state. This result makes sense because, as noted above, the decision to delay payment (i.e., become delinquent) is a necessary condition for default. However, it is important to point out that according to the estimation, Pinnacle's delinquent loans are most likely to transition back to the current state or exit the portfolio (by means other than default) in a year's time. This is likely because problem loans are identified and dealt with via a workout or prepayment rather than allowing them to progress through delinquency to default.

The results also suggest that new loans are most likely to be current a year later

(about 64%), while a fair percentage of new loans can be expected to be retired (about 24%) via prepayment. The former result is obviously what the bank wants, whereas the latter is most likely a function of the time period over which the estimation was made (i.e., a period of generally declining interest rates). In any event, Pinnacle's success as a large agricultural lender can in some way be linked to its ability to generate new loans having a high probability of remaining current or prepaying.

Table 2. Potential Demand Probability Estimates for Pinnacle Bank

d_m ($ millions)	β_m
$100	25.61%
$150	22.43%
$200	19.65%
$250	17.22%
$300	15.09%

The econometric estimation also produces estimates of the size of the bank's pool of loans, reported in Table 2. As shown, the probabilities are not quite uniform (as was the prior probability distribution). Multiplying the parameter support values times the probability estimates and summing gives an estimate of Pinnacle's observed and unobserved loan volume which equals $187 million. The estimate appears reasonable considering Pinnacle's maximum loan volume, achieved in the most recent quarter for which data were available, was $151 million. This result suggests that about $36 million in loan volume was unrealized by Pinnacle over the sample period. However, the normalized entropy is 0.9892, indicating a high degree of uncertainty about the probability distribution of this parameter. Even so, the magnitude of the pool of loans was endogenously determined by the data rather than exogenously by some ad hoc means as in past studies of structural change.

Summary and Conclusions

Because delinquency is a precursor to default, estimating the probability that loans progress through delinquency states is important for the performance measurement and risk management of modern financial institutions. By viewing the bank's portfolio of loans as a Markov chain, it is demonstrated here how maximum entropy can be used to estimate the probability of delinquency which also contains the probability of default and the probability of new loan entry and old loan exit. Most importantly, the estimates can be obtained from publicly available data that are aggregate in nature. Such data are usually all that is available for researchers and investors alike. The model and estimation procedure presented in this study demonstrate how to obtain estimates with aggregated data by employing entropy econometrics.

While numerous techniques for estimating the probability of default have been proposed in the literature, the research outlined in this paper adds to the number of ways by suggesting a minimum cross-entropy formulation of the Markov chain model. The model presented has applicability when micro-level data are available, and therefore likely has usefulness for estimating credit ratings migration matrices and the probability of default, both of which are important for regulatory compliance or Basel consistency.

In addition, a nonstationary matrix of transition probabilities can also be accommodated with the approach we have outlined by making some straightforward adjustments to the estimation procedure. To accomplish this, equation (11) would be minimized subject to equations (4)–(10) for each transition of the data. Employing the 18 quarters of data used for the stationary estimation, nonstationary estimates could be obtained, resulting in 17 transition probability matrices—one for each transition of the data. Further, macroeconomic variables hypothesized to

influence the transition probabilities could also be added to the estimation in both stationary and nonstationary settings. These extensions are left for future research.

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An Analysis of Credit Risk Migration Patterns of Agricultural Loans

Andrew Behrens and Glenn D. Pederson

Abstract

Loan migration analysis is conducted using a large data set of loan risk ratings in the Farm Credit System. We find path dependence and limited support for a trend reversal pattern. There is evidence that the magnitude of migrations reported in previous credit score proxy studies overstates trend reversal in agricultural loans rated by lenders. Our results indicate that retention rates of agricultural loan risk ratings are quite high. Small loans are less likely to migrate than medium- and large-sized loans, and unseasoned loans are more likely to migrate than seasoned farm loans.

Key words: agricultural loans, credit risk migration, Farm Credit System associations, trend reversal

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Migration analysis is a probability-based method for identifying changes in credit risk exposure at the portfolio level. It can also be used to gain insight into the factors that might be motivating those changes. Early studies of risk migration in the U.S. bond market were facilitated by the availability of standard credit risk ratings from Moody's and Standard and Poor's (S&P). A key outcome of this work is the empirical evidence for a downgrade momentum among bond rating migrations. In addition, bond rating migrations were shown to be dependent upon the business cycle (Bangia et al., 2002; Jafry and Schuermann, 2004; Nickell, Perraudin, and Varotto, 2000).

Previous studies of credit risk migration have not directly addressed the question: Why should banks be concerned with the migration of credit risk in their loan portfolios? The emphasis has been largely placed on risk ratings in publicly traded bond markets. Consequently, current models do not adequately explain the importance of credit risk migration in banking.

Although developing an economic model of bank behavior toward risk migration is beyond the scope of this paper, there is a logical relationship between the objective of managing the bank's capital position to remain profitable and the need to monitor and manage credit risk (Bessis, 2005). Losing control of portfolio-level credit risk exposure over time could lead to a deterioration of the return on bank capital. Also, credit risk migration in a loan portfolio poses measurement problems, since these risks may migrate in a systematic way causing overall risk exposure to escalate. For example, this

could occur due to autocorrelation among the transition probabilities or other non-Markov transitions. Thus, bankers might want to know if it is correct to assume that credit risk migration is a stationary Markov process. Providing an answer to this question requires an empirical investigation based on actual loan portfolio data, analogous to what is done in the bond market.

In the absence of sufficient loan portfolio data, credit score proxies have been derived from farm data and used to conduct analyses of agricultural risk migration (Phillips and Katchova, 2004; Escalante et al., 2004). More recently, Gloy, LaDue, and Gunderson (2005) conducted a loan migration analysis on lender-generated risk ratings from a small sample of commercial banks and Farm Credit System associations. A comparison of these agricultural studies suggests that the use of credit score proxies tends to overstate the likelihood of a change in credit risk. As noted by Gloy, LaDue, and Gunderson, a major reason to suspect this variation is that lenders are likely to consider "both financial and nonfinancial factors as well as a borrower's future business prospects" (p. 1) when making credit risk determinations. If one subscribes to the idea that lender-derived loan risk ratings are a true measure of the underlying risk exposure, the implication is that studies which employ credit score proxies potentially suffer from a form of omitted variable bias when measuring credit risk migration patterns.

This study conducts a migration analysis using a large data set of lender-generated credit risk ratings in the Farm Credit System. We seek to explain agricultural credit risk migration by accounting for sources of variability in the risk rating process over time. In order to do this, we examine the influence of previous migrations on future migrations while accounting for attributes of individual loans and the period in which the migration took place. The influence of rating drift on loan migration is explored.

Previous Migration Studies

Barry, Escalante, and Ellinger (2002) use farm data to derive three estimates of credit risk: a credit score, a profitability measure, and a repayment capacity indicator. Five credit classes are considered and different methods of averaging are used to proxy for the credit scoring function. They find that migrations are less likely when credit scores based on averages of annual data are used to determine the initial risk rating and the ending risk rating. The annual retention rates (the probabilities that loans remain in the same risk class) range from 44.1% to 86.9% for averaged credit scores and from 22.9% to 77.2% for credit scores based upon just one year of data. Retention rates of similar magnitudes are found in other agricultural studies utilizing similar credit score proxies and five credit risk classes (Phillips and Katchova, 2004; Escalante et al., 2004). In contrast Gloy, LaDue, and Gunderson (2005) report that annual retention rates range from 84% to 98.6% when lender-generated credit scores and five risk classes are used. The implication is that credit score proxy studies produce generally higher estimates of risk migration.

Bond studies typically use more than five credit risk classes due to the rating granularity provided by Moody's and Standard and Poor's. When using just seven credit risk classes, annual bond rating retention rates typically range from 60% to 92%. Even though the magnitudes of the retention rates differ across the types of data, the pattern does not vary. In every case the lowest retention rates (highest migration rates) occur in the classes representing the lowest levels of credit quality, and the highest retention rates occur in the upper half of the credit quality ratings.

Phillips and Katchova (2004) test for path dependence using the one-year credit score migration rates developed by Barry, Escalante, and Ellinger (2002). Their findings reveal upgrades (downgrades) tend to cause downgrades (upgrades).

Yet, the agricultural credit scoring literature—most notably Novak and LaDue (1997)—has shown that a credit score using only one year of data does not accurately reflect the credit risk characteristics of farms. Averages of multiple years of data tend to smooth the credit score and they are more representative of actual credit risk exposure. Therefore, the pattern of migration trend reversal reported by Phillips and Katchova (2004) is possibly a result of using one-year credit score proxies.

Bond studies of path dependence show a strong downgrade momentum among bonds of high credit quality (Altman and Kao, 1992; Bangia et al., 2002; Lando and Skodeberg, 2002; Wendin and McNeil, 2006; Christensen, Hansen, and Lando, 2004). Bonds that downgraded in a previous period are more likely to downgrade in the following period. The retention rates of previously downgraded bonds are the lowest, and those that upgraded exhibit the highest retention rates (Bangia et al.). In contrast, the evidence to date suggests agricultural loans that previously downgraded have the lowest retention rates, but loans that did not have a previous change in rating also have the highest rate of retention in the subsequent period (Phillips and Katchova, 2004). As shown by this pattern, the one-year credit scores have a tendency to revert to their previous rating. However, it is unclear whether this is representative of the behavior of actual lender-generated credit risk ratings.

Using a five-class rating system, Gloy, LaDue, and Gunderson (2005) perform a logistic regression analysis to detect factors influencing downgrades. Borrower ratings are mapped from the systems used by the lenders providing the data to the five-class system designed by the authors. Due to the expense of collecting the data, the study spans only four years and contains just 589 borrowers. The probability of a downgrade is found to differ across lending institutions. In addition, young borrowers and farm businesses in the declining stage of their business life cycle are more likely to experience a downgrade in credit risk rating.

Data

This study uses loan data from four associations in the Seventh Farm Credit District (AgriBank). The four associations represent large geographic areas in North Dakota, Wisconsin, Minnesota, and Arkansas. The data span the period from December 1997 to June 2004. These associations began risk rating loans on an expanded 14-point scale during 2004 (Anderson, 2004). However, for consistency, the data used in this study are from the period prior to July 2004, when loans were risk-rated on a nine-point scale.[1] The data include semiannual loan credit risk ratings and other loan-specific characteristics. The structure of the data allows for testing of the influence of path dependence, loan size, and loan seasoning by using conditional migration matrices. Semiannual observations of credit risk ratings provide an opportunity to further distinguish the results from those obtained using credit score proxies.

Individual loan observations begin in December 1997, and end in June 2004, yielding a maximum of 14 observation points per loan. The semiannual nature of the data is beneficial because migrations can be monitored more frequently than in previous agricultural studies. In total there are 171,683 loans with multiple observations, although many loans are either not risk-rated or not active. The usable number of observations of loan risk ratings (combining loans across years) is equal to 293,358.

[1] AgriBank FCB sets the definitions and provides guidelines for loan risk ratings, but each association is responsible for the actual implementation of the risk ratings. Behrens (2005) finds that after accounting for other influences, conditioning on the association which rates the loan adds no significant information.

Table 1. Characteristics of the Unused Loan Data and Panel Loan Data

	Unused Loan Data		Panel Loan Data	
Category	**Number**	**Percent**	**Number**	**Percent**
Location of Association:				
North Dakota	6,909.66	3	5,673.24	9
Wisconsin	80,612.70	35	18,910.80	30
Minnesota	128,980.32	56	28,366.20	45
Arkansas	13,819.32	6	10,085.76	16
Loan Type:				
Operating	60,799.90	26	14,983.52	24
Intermediate Term	68,454.84	30	22,310.03	35
Real Estate	96,660.37	42	24,551.29	39
Country Living	4,406.89	2	1,191.16	2
Loan Size:				
Small	142,305	62	45,635	64
Medium	76,089	33	15,899	31
Large	11,928	5	1,502	5
Total Loans:	230,322		63,036	

This data set contains loans that entered the loan database after December 1997, and exited before June 2004. To create a true panel data set, only loans with all 14 observations are used in the analysis, yielding 5,253 usable loans. This produces 63,036 (5,253 × 12) semiannual migrations. The first migration is not a usable observation because its previous migration is unknown. As observed from the descriptive information presented in Table 1, the unused migration data do not differ materially from those included in the study. Both sets of migration data are similar in terms of loan size, loan type, and association representation.

The data set does not contain the date at which each loan's credit risk rating was reevaluated. Without this date it is not possible to determine if there is a rating lag in the data. The credit risk rating of a loan may remain unchanged for a period of time if the lender does not feel there is sufficient evidence to adjust the credit risk rating of the loan. However, even though there are no symptoms of a change in credit quality, a change may have taken place. Knowing the probability that a loan would retain its credit risk rating after a reevaluation would have been a valuable addition to this data set. It is assumed that no change in credit risk rating is either the result of a lack of evidence to change the risk rating or due to changes which are multiple and offsetting. Finally, we cannot differentiate between loans that were reevaluated and those that were not reevaluated.

Measuring Risk Migration

A credit risk migration (or transition probability) is the probability that a loan would end the period with a certain credit risk rating given the credit risk rating at which it began the period. Migration rates are estimated using the following simple calculation:

$$(1) \quad P_{ij} = \frac{n_{ij}}{n_i},$$

where the subscripts i and j represent the initial credit risk rating and the period ending credit risk rating, respectively, n_i is the number of loans that began the period rated i, n_{ij} represents the number of loans

Table 2. Migration Matrix

		Ending Rating									
		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	
Initial Rating	**1**	$\mathbf{P_{1,1}}$	$P_{1,2}$	$P_{1,3}$	$P_{1,4}$	$P_{1,5}$	$P_{1,6}$	$P_{1,7}$	$P_{1,8}$	$P_{1,9}$	$\Sigma = 1$
	2	$P_{2,1}$	$\mathbf{P_{2,2}}$	$P_{2,3}$	$P_{2,4}$	$P_{2,5}$	$P_{2,6}$	$P_{2,7}$	$P_{2,8}$	$P_{2,9}$	$\Sigma = 1$
	3	$P_{3,1}$	$P_{3,2}$	$\mathbf{P_{3,3}}$	$P_{3,4}$	$P_{3,5}$	$P_{3,6}$	$P_{3,7}$	$P_{3,8}$	$P_{3,9}$	$\Sigma = 1$
	4	$P_{4,1}$	$P_{4,2}$	$P_{4,3}$	$\mathbf{P_{4,4}}$	$P_{4,5}$	$P_{4,6}$	$P_{4,7}$	$P_{4,8}$	$P_{4,9}$	$\Sigma = 1$
	5	$P_{5,1}$	$P_{5,2}$	$P_{5,3}$	$P_{5,4}$	$\mathbf{P_{5,5}}$	$P_{5,6}$	$P_{5,7}$	$P_{5,8}$	$P_{5,9}$	$\Sigma = 1$
	6	$P_{6,1}$	$P_{6,2}$	$P_{6,3}$	$P_{6,4}$	$P_{6,5}$	$\mathbf{P_{6,6}}$	$P_{6,7}$	$P_{6,8}$	$P_{6,9}$	$\Sigma = 1$
	7	$P_{7,1}$	$P_{7,2}$	$P_{7,3}$	$P_{7,4}$	$P_{7,5}$	$P_{7,6}$	$\mathbf{P_{7,7}}$	$P_{7,8}$	$P_{7,9}$	$\Sigma = 1$
	8	$P_{8,1}$	$P_{8,2}$	$P_{8,3}$	$P_{8,4}$	$P_{8,5}$	$P_{8,6}$	$P_{8,7}$	$\mathbf{P_{8,8}}$	$P_{8,9}$	$\Sigma = 1$
	9	$P_{9,1}$	$P_{9,2}$	$P_{9,3}$	$P_{9,4}$	$P_{9,5}$	$P_{9,6}$	$P_{9,7}$	$P_{9,8}$	$\mathbf{P_{9,9}}$	$\Sigma = 1$

that began the period rated i and ended the period rated j, and P_{ij} is the migration rate from class i to j during the period.

These migration rates can be conditioned on multiple factors. The most common conditioning criteria are: initial risk rating, direction of migration, and magnitude (distance) of migration. When the loans are conditioned on these three factors, the migration rates can easily be summarized by a migration matrix, as represented in Table 2. A row represents the probabilities of migrating from the initial class to each subsequent credit risk class. The probabilities in each row sum to one. The retention rates are the probabilities on the main diagonal of the matrix. They represent the likelihood that the asset will remain in the same class over the period. Probabilities to the right of the diagonal are downgrades in credit quality, and probabilities to the left are upgrades.

Conditional migration matrices are constructed to test for influential variables. A test of path dependence requires that matrices be conditioned on the direction of the previous migration—downgrade, no change, or upgrade. The conditional matrices are calculated from three subgroups of the data partitioned by the direction of the previous migration. The P_{ij}^{c} terms now contain a superscript to denote the conditioning factor. In this example, conditioning factor superscripts are d (downgrade), nc (no change), or u (upgrade).

A downgrade momentum pattern would be evident if probabilities to the right of the diagonal (downgrades) are larger for loans that previously downgraded than for loans that previously upgraded. An upgrade momentum would result in probabilities to the left of the diagonal (upgrades) which are larger for loans that previously upgraded than for loans that previously downgraded. A trend reversal pattern would be the exact opposite result. Probabilities to the right (downgrades) would be greater for loans that previously upgraded, and probabilities to the left (upgrades) would be greater for loans that previously downgraded. The underlying hypothesis to be tested is:

(2) H_o: $\Pi^{d} = \Pi^{nc} = \Pi^{u}$,

H_a: at least one $\Pi^{c} \neq \Pi^{c'}$.

A chi-square test is employed to determine whether the conditioned matrices differ significantly (Anderson and Goodman, 1957, p. 98). The test statistic is:

$$(3) \quad \chi^2 = \sum_i \sum_{c,j} \left(\frac{n_i^c \left[P_{ij}^c - P_{ij} \right]^2}{P_{ij}} \right),$$

with $m(m - 1)(c - 1)$ degrees of freedom, where m represents the number of rating

classes. A derivation of (3) can be used to identify which row (or rows) cause a rejection of the H_0 in (2). The modified test statistic is:

$$(4) \quad \chi_i^2 = \sum_{c,j} \left(\frac{n_i^c \left[P_{ij}^c - P_{ij} \right]^2}{P_{ij}} \right),$$

with $(m - 1)(c - 1)$ degrees of freedom.

In order to provide a greater level of granularity, a z-test is used to assess the significance of a difference between any two migration rates. If all loans are independent and they all have the same probability of migrating, then P_{ij}^c is a binomial variable with mean Π_{ij}^c and estimated variance

$$(5) \quad s_{P_{ij}^c}^2 = P_{ij}^c \left(1 - P_{ij}^c\right) / n_{ij}.$$

The standard z-test for comparing two independent probabilities is given by:

$$(6) \quad z = \frac{P_{ij}^c - P_{ij}^{c'}}{\sqrt{\frac{s_{P_{ij}^c}^2}{n_i^c} + \frac{s_{P_{ij}^{c'}}^2}{n_i^{c'}}}}.$$

Significance levels are obtained by comparing the z-statistic to the standard normal distribution using two-tailed, pairwise tests.[2]

Results

For both agricultural loan and corporate bond migration analyses, the retention rates that are derived for the highest quality classes are generally the largest (Gloy, LaDue, and Gunderson, 2005; Escalante et al., 2004; Phillips and Katchova, 2004). As shown in Table 3, the same finding holds in this study. However, credit classes 7 and 8 also have high retention rates. This is consistent with the relatively large class 5 retention rates in previous agricultural loan studies. Conversely, the retention rates of the lowest credit quality classes in bond studies tend to be the smallest. We find that the magnitude of the annual loan retention rates correspond with those reported by Gloy, LaDue, and Gunderson. In contrast, our study uses nine risk ratings, so the retention rates found here should be slightly lower than the retention rates reported in those previous studies. Finally, the retention rates reported in credit score proxy studies are typically much lower than the rates documented here. While the migration patterns in credit score proxy studies may still provide useful indicators of trends, the magnitudes of the migrations are not equivalent to those experienced by agricultural lenders.

Path Dependence

If credit risk migrations are not path dependent, the migration matrices should exhibit Markov chain properties. The primary property of a Markov chain is that the transition probabilities are not autocorrelated and only depend on the current risk classification.[3] A more traditional approach to testing for path dependence is to condition the matrices on the direction of the previous period's migrations. The results of conditioning in this way are reported for the annual migration horizon in Table 3. Although not reported here, we note that when a semiannual horizon is used, the resulting pattern appears to be quite similar.

To test for path dependence, the test statistics in equations (3), (4), and (6) are used. The χ^2 statistic, based upon the conditioned annual migration matrices, is 361.5 (the p-value of the statistic is approximately equal to zero at 144 degrees of freedom).[4] Thus, the migration matrices

[2] A bonferroni correction is applied to the significance level of the test to control for multiple testing (Johnson and Wichern, 2002, p. 232).

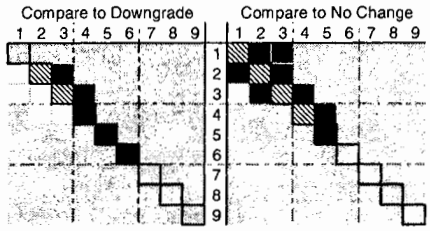
[3] Additionally, if the transition probability function of the Markov process does not depend on t, the process is stationary and the transition probabilities depend only on the interval $h - t$, where $h > t$.

[4] The χ^2 statistic of the conditioned matrices of the 230,322 loans that did not meet the panel data criteria is equal to 450.86. Applying equation (4) shows that initial risk ratings 1–6 are significantly different.

Table 3. Loan Migration When Conditioning on Previous Loan Rating Changes

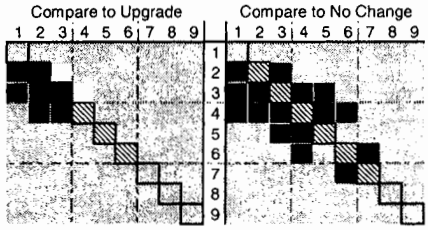
Previous Upgrade

Initial Risk Rating \ Ending Risk Rating	1	2	3	4	5	6	7	8	9	Total
1	85.3	10.4	4.3	-	-	-	-	-	-	517
2	6.6	74.3	16.6	2.3	0.2	-	-	-	-	607
3	0.2	8.3	76.2	14.2	0.8	-	0.4	-	-	529
4	1.3	0.8	8.8	84.9	3.8	-	0.4	-	-	238
5	-	-	-	-	100	-	-	-	-	6
6	-	-	-	9.1	-	81.8	9.1	-	-	11
7	-	-	-	-	-	-	-	-	-	-
8	-	-	-	-	-	-	-	-	-	-
9	-	-	-	-	-	-	-	-	-	-



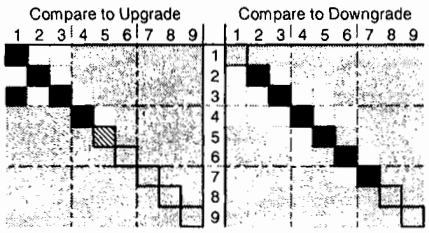
Previous Downgrade

Initial Risk Rating \ Ending Risk Rating	1	2	3	4	5	6	7	8	9	Total
1	-	-	-	-	-	-	-	-	-	-
2	10.1	78.1	9.5	2.3	-	-	-	-	-	483
3	2.4	9.6	78.0	8.6	1.2	0.10	0.10	-	-	967
4	0.9	3.3	13.8	77.4	3.1	1.0	0.5	-	-	876
5	-	0.4	9.1	34.6	50.6	3.0	2.2	-	-	231
6	-	-	1.9	20.4	1.9	63.0	13.0	-	-	54
7	-	-	1.1	9.2	1.1	8.0	80.5	-	-	87
8	-	-	-	-	-	-	-	-	-	-
9	-	-	-	-	-	-	-	-	-	-



Previous No Change

Initial Risk Rating \ Ending Risk Rating	1	2	3	4	5	6	7	8	9	Total
1	89.0	6.9	3.3	0.6	0.12	0.05	0.07	-	-	4179
2	3.6	86.9	7.0	2.1	0.2	0.05	0.08	-	-	6301
3	1.3	5.1	86.8	6.0	0.6	0.09	0.12	-	-	6665
4	0.2	1.9	8.3	86.3	2.3	0.4	0.5	-	-	3728
5	0.3	0.9	5.9	26.0	62.1	2.7	2.1	-	-	338
6	-	0.5	1.6	13.0	2.1	80.3	2.6	-	-	193
7	-	-	1.2	7.2	1.6	4.4	85.2	0.4	-	250
8	-	-	-	-	-	-	-	100	-	5
9	-	-	-	-	-	-	-	-	-	-



Significant differences are measured at $\alpha = 0.05/8$

Significantly Greater Retention Rate
No Significant Difference Retention Rate
Significantly Smaller Retention Rate

are path dependent. However, this result provides no information about the source of path dependence. Performing the same analysis for the rows of each conditioned matrix allows us to determine if path dependence exists throughout the matrices. Table 4 (panel A) reports the χ^2 statistics and corresponding *p*-values for each risk rating of the conditioned matrices. The statistical results indicate that path dependence is confined to risk ratings 2, 3, and 4.

The significant differences reported in Table 3 are not limited to the retention rates. The retention rates of loans that migrated in the previous period (either upgrades or downgrades) are in most instances significantly smaller (or no different) than the retention rates of loans that did not migrate. This indicates either a pattern of momentum or trend reversal.

We find that the initial risk ratings 2 and 3 in the previous upgrade and downgrade matrices show a trend reversal pattern. Previously upgraded loans are less likely to retain their rating and more likely than previously downgraded or unchanged loans to downgrade by one class. Previously downgraded loans are more likely to retain a 2 or 3 rating (than do previously upgraded loans) and they are also more likely to upgrade to ratings 1 and 2, respectively. Risk rating 4 displays a similar pattern with the exception that previously upgraded loans are more likely to retain their ratings than are the previously downgraded loans. These path dependence comparisons reject the null hypothesis in (2), and the observed differences in retention rates are evidence that migration rates differ among loans which have previously upgraded, downgraded, or did not migrate.

Table 4. Path Dependence Test Results by Risk Rating

Risk Rating	PANEL A: Conditioning on Previous Migration (annual horizon)		PANEL B: Conditioning on Loan Size (semiannual horizon)		PANEL C: Conditioning on Loan Seasoning (semiannual horizon)	
	χ^2	*p*-Value	χ^2	*p*-Value	χ^2	*p*-Value
1	13.9	0.609	44.1	0.000	49.1	0.000
2	135.1	0.000	112.6	0.000	40.2	0.000
3	121.7	0.000	114.8	0.000	23.9	0.002
4	60.5	0.000	79.0	0.000	24.5	0.002
5	14.1	0.591	100.0	0.000	14.3	0.074
6	13.7	0.622	15.7	0.472	22.8	0.004
7	2.5	1.000	18.8	0.300	15.1	0.100
8	0.0	1.000	0.0	1.000	0.5	1.000
9	0.0	1.000	485.0	0.000	190.4	0.000
	DF = 16		DF = 16		DF = 8	

These results generally support a trend reversal pattern among loans that begin a period with an "acceptable" risk rating (1–4).[5]

Loan-Specific Characteristics

Credit score proxy studies do not account for loan-specific characteristics. Yet, these characteristics may be a strong motivation for lenders to undertake migration analyses. Since credit score proxies are computed from farm financial statements, they may incorporate independent variables such as borrower age or farm type into the analysis, but it may not be possible to account for other factors that are loan specific. In this study we can account for two such factors—loan size and loan seasoning. Lenders would clearly like to know what impact these factors have on loan migration due to their implications for risk exposure of the lending institution.

The perception of loan size is expected to vary from lender to lender, and by whether one takes a "borrower-level" or "loan-level" perspective. For this study AgriBank assisted in setting the loan size thresholds. At the borrower level, loan amounts less than $250,000 are classified as small loans, while those greater than $1,000,000 are classified as large loans.[6] The size of home mortgages is based upon the amount at the individual loan level. During the study period, a "jumbo or nonconforming" mortgage is defined as a loan with principal exceeding $360,000. Thus, jumbo mortgages are classified as large loans.

The application of equation (3) to the data in Table 5 results in a value of 485.0 (the *p*-value of the statistic is approximately zero at 144 degrees of freedom). The row-by-row analysis indicates that after conditioning on loan size, the initial risk ratings 1–5 and 9 account for significant differences from results reported for the unconditioned matrix (see Table 4, panel B).

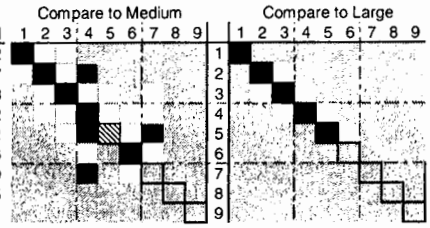
[5] Migration rates were also found to be dependent upon the previous period's migration using a log-linear model. The log-linear model tests for significant differences between entire matrices or tables that are conditioned on the previous period's migration rather than the individual cells of the matrices.

[6] To test the sensitivity of the results to changes in the definition of size, the definition of a small loan was changed to those total loan amounts less than $100,000. Total loan amounts between $100,000 and $250,000 were then considered medium-sized loans. The resulting χ^2 statistics indicate the same levels of significance as shown in Table 4.

Table 5. Loan Migration When Conditioning on Loan Size

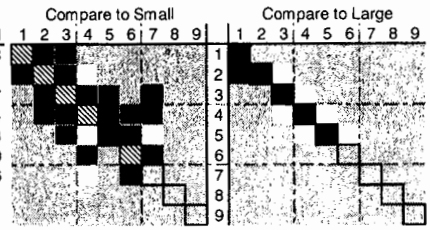
Small

Initial Risk Rating \ Ending Risk Rating	1	2	3	4	5	6	7	8	9	Total
1	90.0	6.4	2.8	0.5	0.14	0.05	0.08	-	-	3652
2	3.6	87.3	6.6	2.2	0.2	0.05	0.09	-	-	5637
3	1.3	4.9	87.6	5.5	0.5	0.07	0.09	-	-	5708
4	0.5	1.7	7.7	87.3	2.0	0.4	0.5	-	-	3292
5	0.3	1.1	6.3	32.4	56.5	0.6	2.8	-	-	352
6	-	0.5	1.5	13.3	1.5	80.1	3.1	-	-	196
7	-	-	0.8	9.6	1.2	3.6	84.3	0.4	-	249
8	-	-	-	-	-	-	-	100	-	5
9	-	-	-	-	-	-	-	-	-	-



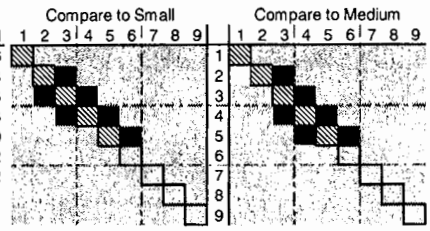
Medium

Initial Risk Rating \ Ending Risk Rating	1	2	3	4	5	6	7	8	9	Total
1	84.0	10.2	5.5	0.3	-	-	-	-	-	1018
2	6.7	79.2	12.0	1.9	0.2	-	-	-	-	1631
3	1.5	8.0	79.5	9.5	1.2	0.09	0.27	-	-	2197
4	0.3	2.8	12.0	80.1	3.3	0.8	0.7	-	-	1374
5	-	-	9.4	22.7	63.5	3.4	1.0	-	-	203
6	-	-	2.0	22.0	2.0	64.0	10.0	-	-	50
7	-	-	2.3	1.2	2.3	10.5	83.7	-	-	86
8	-	-	-	-	-	-	-	-	-	-
9	-	-	-	-	-	-	-	-	-	-



Large

Initial Risk Rating \ Ending Risk Rating	1	2	3	4	5	6	7	8	9	Total
1	76.9	15.4	7.7	-	-	-	-	-	-	26
2	4.1	72.4	18.7	4.1	0.8	-	-	-	-	123
3	1.2	7.4	76.2	13.7	1.2	0.39	-	-	-	256
4	-	2.8	19.3	71.0	6.3	0.6	-	-	-	176
5	-	-	-	40.0	25.0	35.0	-	-	-	20
6	-	-	-	-	8.3	75.0	16.7	-	-	12
7	-	-	-	50.0	-	-	50.0	-	-	2
8	-	-	-	-	-	-	-	-	-	-
9	-	-	-	-	-	-	-	-	-	-



Significant differences are measured at $\alpha = 0.05/8$

Significantly Greater — Retention Rate
No Significant Difference — Retention Rate
Significantly Smaller — Retention Rate

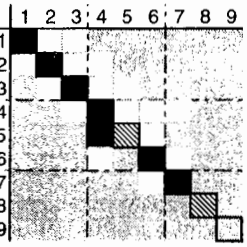
As reported in Table 5, most of the significant differences occur along the main diagonals of the matrices. Small loans are significantly less likely to migrate than either medium- or large-sized loans. It is also true that medium-sized loans are less likely to migrate than large loans. The significance of differences between upward and downward migrations is not directional. The off-diagonal patterns simply reinforce the retention rate patterns. Although it is not clear, one hypothesis is that these results may be due to differences in the amount of time devoted by lenders to evaluating small-, medium-, and large-sized loans. Underwriting a large loan is expected to require more time. Also, larger loans are likely to be monitored more closely, resulting in more frequent evaluations and the opportunity for more frequent risk rating adjustments.

Another anomaly continually appearing in these migration matrices is the low retention rate of risk class 5. Recall that risk class 5 is the highest quality rating which is not considered "acceptable" credit quality. One explanation for the observed low retention rate is that lenders may monitor these loans more closely. The greater monitoring expenses on these loans may bring an added benefit in the form of lower required reserves when an upward rating adjustment is made. Anomalies of this type likely would only be evident in lender-generated risk ratings and would not be evident in credit score proxy studies of risk migration. When assessing the class 5 anomaly on loan size, it appears that only small loans have an unusually low class 5 retention rate and an unusually high $P_{5,4}$ (probability of a higher rating).

Table 6. Loan Migration When Conditioning on Loan Seasoning (3 years past origination)

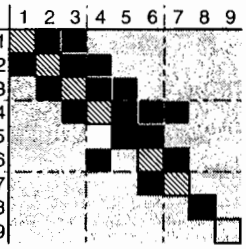
Seasoned

Initial Risk Rating	Ending Risk Rating 1	2	3	4	5	6	7	8	9	Total
1	92.6	4.9	2.0	0.4	0.04	0.02	0.03	-	-	10773
2	2.6	91.1	5.0	1.2	0.12	0.02	0.05	-	-	16491
3	0.9	3.4	91.1	4.0	0.4	0.06	0.07	-	-	17566
4	0.2	1.1	5.5	91.0	1.6	0.3	0.2	-	-	10411
5	0.5	0.2	4.1	17.1	75.1	1.6	1.4	-	-	1254
6	-	0.2	1.2	11.4	1.2	83.4	2.7	-	-	590
7	-	-	0.4	4.5	1.1	2.3	91.4	0.3	-	708
8	-	-	-	-	-	-	11.1	89	-	9
9	-	-	-	-	-	-	-	-	-	-



Unseasoned

Initial Risk Rating	Ending Risk Rating 1	2	3	4	5	6	7	8	9	Total
1	86.7	8.5	3.8	0.7	0.4	-	-	-	-	850
2	3.7	86.3	7.6	2.1	0.3	0.07	-	-	-	1465
3	1.0	3.8	88.2	5.9	0.9	0.12	0.12	-	-	1722
4	-	1.4	6.2	88.7	2.2	0.6	1.0	-	-	1023
5	-	1.3	6.5	6.5	79.2	5.2	1.3	-	-	77
6	-	-	4.1	22.4	2.0	59.2	12.2	-	-	49
7	-	-	-	-	-	11.4	88.6	-	-	44
8	-	-	-	-	-	-	-	100	-	4
9	-	-	-	-	-	-	-	-	-	-



Significant differences are measured at $\alpha = 0.05/8$

Significantly Greater — Retention Rate
No Significant Difference — Retention Rate
Significantly Smaller — Retention Rate

A seasoned loan is initially defined, with guidance from AgriBank, as a loan that is three years past its date of origination. Table 6 depicts the matrices conditioned on seasoning and any significant differences. The χ^2 statistic is 190.4 (the *p*-value of the statistic is 0.0058 with 72 degrees of freedom). Thus, conditioning on loan seasoning produces migration matrices that are statistically different from the unconditioned matrix.

As reported in Table 4 (panel C), we can compare the matrices by row. We find significant deviations from the unconditional matrix in the initial risk ratings 1–4, 6, and 9. Like the loan size results, this pattern appears to be driven by retention rates. The matrices imply that unseasoned farm loans are more likely to migrate than seasoned farm loans. This is evident from a comparison of the retention rates along the main diagonals of the matrices, and the probabilities of one-class upgrades and one-to-two class downgrades. By comparison, the retention rates are lower in the unseasoned matrix.

The 1 and 2 risk class migration rates are greater for the unseasoned loans, irrespective of the direction of migration. One possible explanation is that by the time a loan has been in the portfolio for three years, the lender may have been able to collect more accurate information on the borrower, and future cash flows of the borrower may have become less uncertain. Thus, a comparison of migration matrices at three years past origination reveals that the ratings of new farm loans are more volatile than those of seasoned farm loans.

Use of a three-year cutoff date to define seasoned loans is a subjective decision, and lenders may want to know how sensitive risk migration is to the length of seasoning. For example, are loans at two years more likely to migrate than loans at three years? Since shortening or lengthening the cutoff date from three years may alter the pattern of migration and its significance, a sensitivity analysis of loan seasoning is conducted by varying the number of years post-origination, and observing the retention rates of different

risk classes. The results indicate that the three-year seasoning pattern also occurs for these other seasoning periods. The pattern of significance shown for a three-year cutoff period is consistent with that found when using a cutoff period ranging from 1.5 to 4.5 years. Yet, there are slight variations in the significance of multiple class migrations. Thus, regardless of the seasoning period, the probability of a downgrade is greater for unseasoned loans than for seasoned loans.

Finally, an anomaly is observed in the significance pattern that occurs among loans initially risk-rated 5. Class 5 seasoned loans are less likely to retain their rating and more likely to upgrade until the seasoning cutoff period is raised to seven years. For cutoffs of seven years, the retention rates of seasoned and unseasoned risk-rated 5 loans are not significantly different. Seasoned loans are less likely to retain their initial risk rating when the cutoff period is set between 8–10 years. These results indicate that the anomaly among the migration rates of risk-rating 5 loans is due to characteristics of loans that are more than 1.5 years past their origination date. Furthermore, the results from loan size conditioning indicate that the class 5 anomaly occurs among small loans that are more than 1.5 years past their origination date.

Conclusions

A limited trend reversal pattern is supported by the risk migration patterns found in this study. We also find that the magnitude of migrations reported in previous studies using credit score proxies in place of lender risk ratings, appear to overstate the degree of trend reversal that has existed for agricultural loans rated by lenders. The results obtained here show that retention rates of agricultural loan risk ratings are quite high. This finding is consistent with the previous study by Gloy, LaDue, and Gunderson (2005), which also used agricultural loan risk rating data.

There is reasonably strong evidence of path dependence in the risk rating migrations reported in this study. The derived migration matrices clearly do not follow a stationary Markov chain process. The extrapolated migration matrices have lower retention rates than actual migration matrices measured over the same time horizon. This result supports trend reversal. Comparisons of the retention rates of loans conditioned on the direction of the previous migration show loans that migrated in the previous period are more likely to migrate in the next period. These results support an earlier finding of trend reversals among credit score proxy risk ratings. However, we are only able to confirm the statistical significance of the pattern in high credit quality classes.

We find that small loans are less likely to migrate than medium- and large-sized loans when the loans are risk rated by lenders. New, unseasoned farm loans are more likely to migrate than seasoned farm loans.

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Markov Chain Models for Farm Credit Risk Migration Analysis

Xiaohui Deng, Cesar L. Escalante, Peter J. Barry, and Yingzhuo Yu

Abstract

This study introduces two Markov chain time approaches, time-homogeneous and nonhomogeneous models, for analyzing farm credit risk migration as alternatives to the traditional discrete-time (cohort) method. The Markov chain models are found to produce more accurate, reliable transition probability rates using the 3 × 1 migration measurement method used by farm lenders. Compared to corporate bond ratings migration results, this study obtained larger mean differences in singular value decomposition between the cohort matrix and each of the Markov chain matrices. This finding suggests that the omission of transient, indirect migration activities under the cohort method is more costly when applied to farm credit analysis. This discrepancy could lead to understated transition probability estimates which, in turn, could produce misleading indicators of farm loan portfolio quality.

Key words: cohort method, continuous time models, credit risk migration, Markov chain process, semi-parametric multiplicative hazard model, time homogeneity, transition probabilities

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Review coordinated by Calum G. Turvey.

In corporate finance, migration analysis has been employed extensively as an important analytical decision aid for investors, lenders, and asset managers. Major rating companies such as Moody's and Standard and Poor's have routinely measured and reported rating migration rates for bonds and other publicly traded securities. Transition or migration analysis is based on the extrapolation into the future of historic rates of movement (i.e., transition probabilities) among risk rating classes. The decision tool, a summary migration matrix, is a compilation of longitudinal (time-series) averages of transition rates from matrices for subsets of shorter time periods. The time period matrices, in turn, are constructed from a panel transitions data set. Analysts and investors use such matrices to determine likelihoods of intertemporal changes in the quality of bond and security issues that are factored into portfolio risk management decisions.

Migration analysis is essential to the credit risk component of economic capital management employed by the top tier of financial institutions and recently adopted by the new Basel Accord as the vanguard method of determining regulatory capital (Saunders, 1999; Altman, 1998). Commercial lenders use transition rating matrices to develop probability estimates of financial stress/loan default rates and other indicators of their loan portfolio quality. Migration rates for commercial loans, agricultural loans, and other types of loans, however, are more difficult to compile due to shorter data histories, less updated term loan underwriting histories, and use of relatively newer risk rating systems (Barry, Escalante, and Ellinger, 2002). Nonetheless, credit rating

transition rates offer richer, broader information on risk stability and loan portfolio quality than historic loan default rates derived using traditional measurement methods (Katchova and Barry, 2005).

Credit migration analysis is still a relatively unexplored concept in farm finance, although a number of farm lenders, such as the Farm Credit System institutions, are compiling the data needed to use migration as a tool for analyzing their loan portfolios. Barry, Escalante, and Ellinger (2002) introduced the measurement of transition probability matrices and financial stress rates for farm businesses using several time horizons and credit risk classification variables. Sherrick, Barry, and Ellinger (2000) used credit value-at-risk (VaR) techniques to calculate empirical estimates of the cost of insuring against credit risk in pools of agricultural mortgage loans.

Katchova and Barry (2005) have demonstrated the application of the CreditMetrics migration model in estimating farm lenders' economic capital requirements to protect them against unexpected losses and provisions for allowances to cover expected losses under the new Basel Accord. Another study applied ordered logit techniques to a panel farm-level data set to identify significant determinants of farm credit migration probabilities among demographic, financial performance, and macroeconomic variables (Escalante et al., 2004). Phillips and Katchova (2004) also tested for the presence of rating drift by conditioning farm transition rates on business cycles and previous migration trends.

These studies, along with most related published works in corporate finance, usually employed a straightforward discrete-time (cohort) approach in developing migration matrices, which has even become an "industry standard" approach used by the large corporate rating agencies (Lando and Skodeberg, 2002; Schuermann and Jafry, 2003). Notably, the cohort approach ignores any rating change activity within subperiods of a given time frame and focuses only on migrations observed at the two time endpoints (i.e., the beginning and the end of a time period). The omission of such "transient" class migrations reduces the reliability of the cohort approach in consistently producing accurate and efficient estimates of migration rates.

Several studies in the area of corporate finance have adopted a duration "Markov chain" approach based on survival analysis to address the deficiency of the cohort method (Lando and Skodeberg, 2002; Israel, Rosenthal, and Wei, 2001). Our study applies the same Markov chain model variants used in those analyses (time-homogeneous and nonhomogeneous Markov chain models) to the estimation of farm credit risk migration rates using farm-level financial data from the Illinois Farm Business Farm Management (FBFM) system. The farm data are tested initially for conformity with the Markov property of independence, a precondition for the adoption of such models. These tests include eigenvalue/vector analyses and a semi-parametric multiplicative hazard model to test for the existence of rating drift that violates the Markov chain assumption.

In corporate bond applications, the Markov chain approach has been used to capture intra-year risk-rating changes to calculate annualized migration rates, which are then averaged across time periods to construct an overall (summary) migration matrix. Formal ratings and re-ratings generally occur annually even though true changes in risk occur more frequently. The intra-year bond migration rates help to fill this information gap.

In farm finance where farmers do not maintain records of intra-year changes in financial conditions, the Markov chain approach could be applied to the treatment of annualized migration rates in constructing the migration matrix for each time period. This modification is relevant considering that actual credit risk transition assessment practices by farm

lenders usually lean toward averaging of multi-year financial ratios and measures (Novak and LaDue, 1997).[1] For instance, one such method acknowledged by lenders is the 3 × 1 method which measures the transition from a credit rating based on the average financial performance during the first three years to the risk rating given to the borrower on the fourth year (Barry, Escalante, and Ellinger, 2002).[2]

The practical relevance of introducing the alternative Markov chain models for farm credit risk migration analysis is established through the following arguments.

- First, while annual data are generally used in the re-rating process, a lender's monitoring of a borrower's performance can reveal likely changes in farmers' risk positions during the year, i.e., marking risk to changes in growing and/or market conditions, especially for higher risk borrowers. Thus, subjective transitions may occur much more frequently, and the Markov process helps in quantifying such movements.
- Second, our study's findings will show that multi-year averaging of annualized financial data and the discrete-time (cohort) framework used in developing the summary migration matrix can result in the significant understatement of transition probability rates.
- Third, such probability estimates would, in turn, produce understated, if not misleading, estimates of overall portfolio default probability rates, which is one of several loan portfolio quality indicators that lenders could generate from the migration framework (Katchova and Barry, 2005).
- Finally, our statistical test results reveal that distinctions between cohort and Markov chain matrices are even more pronounced when applied to farm finance conditions than when applied in corporate bond analysis.

In this analysis, we start with a 2 × 1 migration framework[3] to lay out the theoretical strengths and arguments of the proposed alternative Markov chain models.[4] The lenders' 3 × 1 migration framework is later used to verify the merits of the alternative methods. The 2 × 1 method tracks the migration of the credit rating assigned to the average financial measures of the first two years to the credit rating on the third year. The 3 × 1 method, on the other hand, uses the credit rating assigned to the average financial performance of the first three years as the starting point.

The remainder of the article proceeds as follows. The next two sections provide a description of this study's farm financial data set and demonstrate the estimation of an aggregate cohort migration matrix using the 2 × 1 measurement method. The subsequent section tests for validity of the Markov chain process assumption as applied to this study's farm credit risk migration data set. The next sections then present the estimation of the Markov chain matrices, develop portfolio default

[1] According to Novak and LaDue (1997), "In practice, agricultural lenders generally do not flip-flop credit decisions on an annual basis, but rather deal with normal fluctuations in farm income on an individual borrower and commodity basis. One method used by lenders to objectively ameliorate such annual fluctuations, not only in debt repayment capacity, but more generally in income-based financial ratios and measures, is to calculate and evaluate a borrower's multiyear average financial ratios and measures" (p. 39).

[2] Aside from the 3 × 1 method, farm lenders also use the 2 × 2 and 3 × 3 methods where the transitions are based on the average credit score of the first two (three) years and its migration to a credit score based on the average of the last two (three) years in a three- (four-) year period (Barry, Escalante, and Ellinger, 2002).

[3] There is no evidence that the 2 × 1 method is actually used by farm lenders. However, since it is a simpler variant of the 3 × 1 method actually used by farm lenders, it is being adopted here merely to illustrate the theoretical arguments of the Markov chain model.

[4] The testing and application of the Markov chain process will require at least three years of consecutive annual data for each farm. In each three-year period, the 2 × 1 method is the simplest migration measurement approach that is consistent with the farm lenders' practice of analyzing risk migration from multi-year averages to a one-year transition horizon (such as the fourth year in the 3 × 1 method).

probability estimates under the cohort and Markov chain models, use the farm lenders' 3 × 1 method to validate earlier findings, and discuss overall implications of the models' results. Concluding remarks are given in the final section.

Farm Credit Risk Ratings Data

In the absence of lender data, this study utilizes farm-level financial data as a proxy for actual loan performance.[5] These financial data come from a database of certified usable annual farm financial and family living records compiled under the Illinois FBFM system for the period 1985 to 2001. While the FBFM system has an annual membership of about 7,000 farms, stringent procedures enforced for the certification of the soundness and acceptability of both sets of financial and family living records usually reduce the database to about 500 to 1,500 farms in each year.

For purposes of this analysis, we initially considered selecting only those farm observations that have been consistently certified by the FBFM throughout the 17-year period. However, this approach significantly reduced the sample size. Hence, this study instead utilizes unbalanced annual data sets where sample composition was allowed to vary over time periods to include farms that were not present in most other time period data sets. Previous studies have employed this approach to ensure a sample size large enough to produce statistically reliable results (Bangia et al., 2002; Barry, Escalante, and Ellinger, 2002).

The credit risk classification variable used in this analysis is a farm's risk rating determined through a uniform rating model for term loans as reported by Splett et al. (1994). This model was developed for the Sixth Farm Credit District lenders in the early 1990s using a joint experience and statistical approach. Five financial ratios recommended by the Farm Financial Standards Council representing a farm's solvency, repayment capacity, profitability, liquidity, and financial efficiency are used in this model. The measurement procedures, predetermined weights assigned to each component of the rating model, and the intervals used to classify the scores into five credit classes (where class 1 is the most favorable, lowest risk rating class and class 5 is the highest risk rating, default class)[6] as specified in Splett et al. (1994) are used in this analysis (see also Barry, Escalante, and Ellinger, 2002; Escalante et al., 2004).

Developing the Cohort Migration Matrix

The cohort method, which calculates migration rates under a discrete-time framework, is currently the standard approach used by most industry rating companies. It has been employed in several earlier migration studies in the corporate and farm finance literature. Under this method, migration rates are calculated over a specific time horizon Δt by considering the change from N_i farm observations that belong to rating category i at the start of the time horizon to N_{ij} farms that migrate to rating category j at

[5] Use of farm record data as a proxy for lender data could yield higher rates of transition across risk classes due to the omission of the influence of lenders' discretionary judgment that could stabilize movements among risk classes as well as their use of risk mitigation techniques in developing loan packages, and the inclusion of non-borrowing farms which might not meet lenders' credit risk assessment standards (Barry, Escalante, and Ellinger, 2002). In the absence of more reliable, longitudinal farm lender data, however, most studies in farm finance have used farm record data as lender data proxy (Barry, Escalante, and Ellinger, 2002; Phillips and Katchova, 2004; Katchova and Barry, 2005).

[6] Class 5 farms include both those in "default" or other cases of high credit risk. Since the sample composition is allowed to vary in this study from each three-year grouping to another, defaulting farms in a particular period most likely have not remained in the database when the successive groups of observations are determined. These cases are analogous to those belonging to the "withdrawn" rating class used by S&P and Moody's.

the end of the time horizon. The probability estimate, $\hat{P}_{ij}^{\Delta t}$, which corresponds to the probability of migrating from category i to category j over Δt, is expressed as:

$$(1) \quad \hat{P}_{ij}^{\Delta t} = \frac{N_{ij}}{N_i}.$$

In any given period, the migration possibilities for each farm are either upward migration to a more favorable risk rating category, downward migration to a higher risk category, or retention in its current rating class.

Several potential measurement approaches represent different amounts and time sequences of data employed in the measurement process (Barry, Escalante, and Ellinger, 2002). Empirical works on corporate bond migration usually employ the year-to-year transition approach (movement from a year t to a year $t+1$ classification). This study initially uses the 2×1 measurement approach (movement from credit class based on the average of years t_1 and t_2 to risk rating in t_3) to introduce and develop the proposed alternative migration frameworks.

This measurement approach is the simplest version of the farm lenders' multi-year averaging approach in tracking migration to a one-year horizon. Later, we adopt the 3×1 approach actually used by farm lenders that measures the transition from a credit score rating based on the average of the first three years to the risk rating given to the borrower on the fourth year (Barry, Escalante, and Ellinger, 2002), to validate the strengths and relevance of our proposed models.

Given the sample farms in this analysis, the 2×1 approach resulted in 15 migration matrices, constructed from data on three consecutive years, over the 17-year sample period. A data set for each three-year period consists of farms that were consistently in the FBFM record system during those three consecutive years. This procedure produced a total of 8,751 farm observations for all 15 three-year groupings (details of the breakdown are presented later in Table 5).

The transition rates are calculated based on the farms' risk classifications using the average financial data for the first two years (t_1 and t_2) and the risk classifications at t_3. The averages of the transition rates calculated for each of the 15 three-year groupings are then summarized into an overall unconditional transition matrix reported in Table 1, where the diagonals correspond to the retention rates and the matrix elements above (below) the diagonal represent downward (upward) migration. This summary transition matrix therefore represents credit risk migration tendencies over the entire sample period from which loan portfolio quality indications can be deduced.

Time Measurement Issues and the Markov Chain Process

Time horizon measurement is an important consideration in migration analysis. Normally, fewer rating changes are omitted when using shorter time horizons. However, shorter duration could also result in lower rating volatility enhanced by the interplay of business cycle effects. Moreover, shorter duration is subject to "noise" which would eventually be cancelled out in the long term (Bangia et al., 2002). More longitudinal, detailed data histories in corporate finance allow for migration studies to analyze time horizons that are shorter than one year.

Farm finance studies on migration, however, must contend with limited data histories that are more aggregated since farmers do not maintain records of intra-year changes in financial conditions. Moreover, farm lenders usually resort to averaging of multi-year financial ratios and measures (Novak and LaDue, 1997), such as the 3×1 method described earlier.

In this study we adopt a duration "Markov chain" approach based on survival analysis that has been used in corporate finance studies to factor in intra-year changes in risk ratings in constructing year-to-year transition matrices (Lando and Skodeberg, 2002; Israel, Rosenthal, and Wei, 2001).

Table 1. Summary 2 × 1 Transition Matrix Under the Cohort (discrete-time) Method, 1985–2001 (percent)

Period 1 Farm Credit Risk Classes	Period 2 Farm Credit Risk Classes				
	1	2	3	4	5
1	75.14	16.47	6.53	1.75	0.11
2	24.68	43.52	19.69	10.14	1.97
3	12.23	27.39	39.70	14.46	6.21
4	3.57	24.49	35.16	27.43	9.36
5	0.25	9.21	37.78	24.98	27.79

In our analysis the Markov chain process is applied to the treatment of annualized migration rates in determining migration matrices for each time period that altogether determine a farm loan portfolio's summary migration matrix. This approach is expected to produce more reliable, accurate transition probability estimates than those obtained by farm lenders using multi-year averaging of annualized financial data under the cohort method.

A Markov process is a sequence of random variables $\{X_t \mid t = 0, 1, 2, \ldots\}$ with common space S whose distribution satisfies

$$(2) \quad \Pr\{X_{t+1} \in A \mid X_t, X_{t-1}, X_{t-2}, \ldots\} = \Pr\{X_{t+1} \in A \mid X_t\}, \quad A \subset S.$$

In this process, movement from one state to another is dependent (only) on what occurred in the previous n states. The number of previous states (n) affecting the choice in the current state determines the order (n) of the process (Voskoglou, 1994). Here we consider the first-order process where the current state is influenced solely by the previous state. Using equation (2), the distribution of X_{t+1} conditional on the history of the process through time t is completely determined by X_t and is independent of the realization of the process prior to time t. A Markov chain is a process with a finite state-space $S = \{1, 2, 3, \ldots, n\}$ and is completely characterized by its transition probabilities:

$$(3) \quad P_{ij} = \Pr\{X_{t+1} = j \mid X_t = i\}, \quad i, j \in S.$$

Most corporate finance studies that adopt the Markov chain process in transition probability modeling have assumed their data sets' compliance with the first-order Markov process without performing the necessary validating tests (Jarrow, Lando, and Turnbull, 1997; Schuermann and Jafry, 2003). Phillips and Katchova (2004) tested for the Markov chain property of a sample of Illinois FBFM farms for the same 17-year period used in this study. Using an overall singular value metric test to determine significant differences between unconditional and conditioned matrices (which will be discussed in detail later), their results indicate the violation of the Markov property of independence and established significant trend reversal tendencies, a reverse form of path dependence. In this study, we validate the presence of Markovian behavior in the Illinois farm data set using two test methods: eigenvalue/vector analysis and semi-parametric multiplicative hazard tests.

Analysis of Eigenvalues and Eigenvectors

The analysis of eigenvalues and eigenvectors[7] has been a widely used approach to test the Markovian property of

[7] Eigenvalues are a special set of scalars (also known as characteristic roots) associated with a linear system of equations such as a matrix equation. Each eigenvalue is paired with a corresponding eigenvector. Any square matrix has at least one nonzero vector $\mathbf{v}$ such that $M\mathbf{v} = \lambda\mathbf{v}$. In this case, $\mathbf{v}$ is said to be an eigenvector of the matrix with an eigenvalue λ.

a matrix (Bangia et al., 2002). The information of any transitional matrix could be divided into its eigenvalues and eigenvectors, written as:

$$(4) \quad \mathbf{P} = \mathbf{U}_{n \cdot n} \mathbf{\Lambda}_{n \cdot n} \mathbf{U}^{T}_{n \cdot n},$$

where **P** is the transitional matrix; **Λ** is a diagonal matrix where each element on the diagonal represents one eigenvalue of **P**; T is the time horizon; and **U** is a matrix with columns u_1, u_2, ..., u_n representing **P**'s eigenvectors that correspond to each element of **Λ**. Moreover, any transition matrix can be taken to the kth power by increasing its eigenvalues to its kth power while leaving its eigenvectors unchanged.

This will modify the above **P** expression (4) into:

$$(5) \quad \mathbf{P}^{k} = \mathbf{U}_{n \cdot n} \mathbf{\Lambda}^{k}_{n \cdot n} \mathbf{U}^{T}_{n \cdot n}.$$

Under this approach, two conditions must be satisfied to confirm that the transition matrices follow the Markov chain process. In this study, we test these conditions following the analytical framework used by Bangia et al. (2002). The first condition requires that eigenvalues (e_i) should "decay exponentially" with increasing time horizons. This can be shown graphically by ranking the eigenvalues of the transition matrices in the order of their magnitude. A linear relationship between $\log(e_i)$ and time horizon T in these plots would provide evidence of Markovian behavior.

The second condition requires an identical set of eigenvectors for all transition horizons. This can be verified graphically by separately plotting for each transition horizon the eigenvector element values against the different rating categories considered in the empirical transition matrices. The existence of the Markovian property in the data set is verified if identical plots are obtained for the different time horizons. Bangia et al. (2002) applied this criterion by analyzing the plots of the second eigenvector of matrices for different transition horizons.[8]

Figure 1 presents a plot of the second to fifth eigenvalues of the empirical matrices with transition horizons varying from one to four years. The calculated eigenvalues show a strong log-linear relationship over the increasing transition horizons, thus providing evidence that farm credit migration rates tend to follow the Markov chain process. This finding is corroborated by the results of the eigenvector analysis presented in Figure 2. The plots provide the trends of second eigenvector values for the transition matrices across rating categories using different time horizons. The similarity of the second eigenvector plots again fails to reject the Markov chain process assumption. Notably, our results are consistent with the findings of Bangia et al. (2002).

Semi-Parametric Multiplicative Hazard Model

A second test of the Markovian property uses a quantifiable measure to confirm the trends in the earlier eigenvalue and eigenvector graphs. The semi-parametric multiplicative hazard (SPMH) approach can detect the incidence of Markovian behavior in every possible direction of a rating migration instead of calculating an overall statistic for matrix comparisons [such as the singular value metric test employed by Phillips and Katchova (2004)].

The SPMH framework used in this study is based on the testing procedures used by Lando and Skodeberg (2002) in their bond migration analysis. The key assumption is

[8] The choice of the second eigenvector is justified as follows. All transition matrices have at least one eigenvalue of *unity*, which is of the highest magnitude and stems from the nature of transition matrices where the sum of the row elements is equal to one. The remaining eigenvalues have magnitudes smaller than *unity*. The *unity* eigenvalue implies that the transition matrix will decay to steady state eventually and the second largest eigenvalue provides an indicator of the speed of such decay (Jafry and Schuermann, 2003).

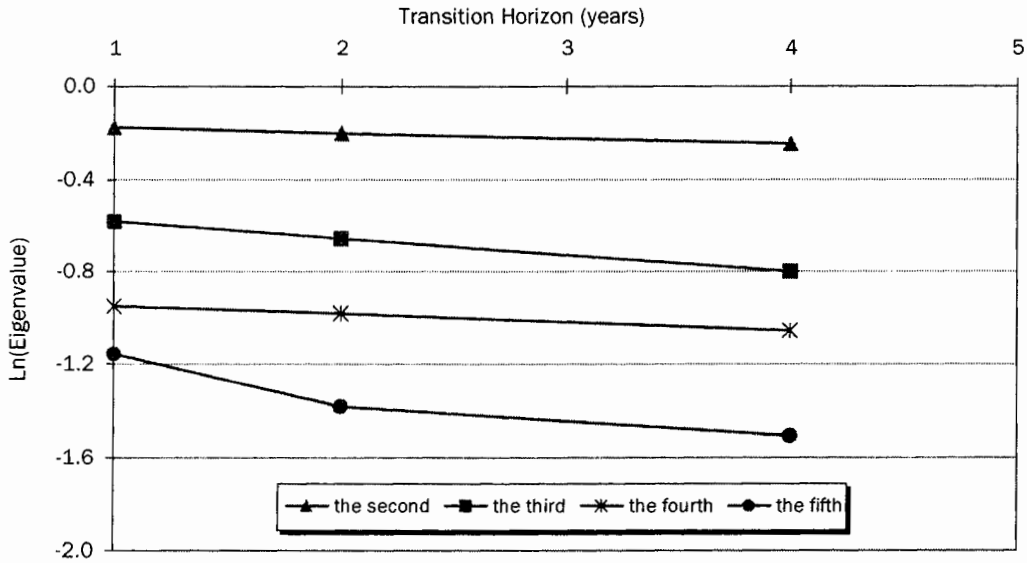

Figure 1. Decay of Eigenvalues with Different Transition Horizons

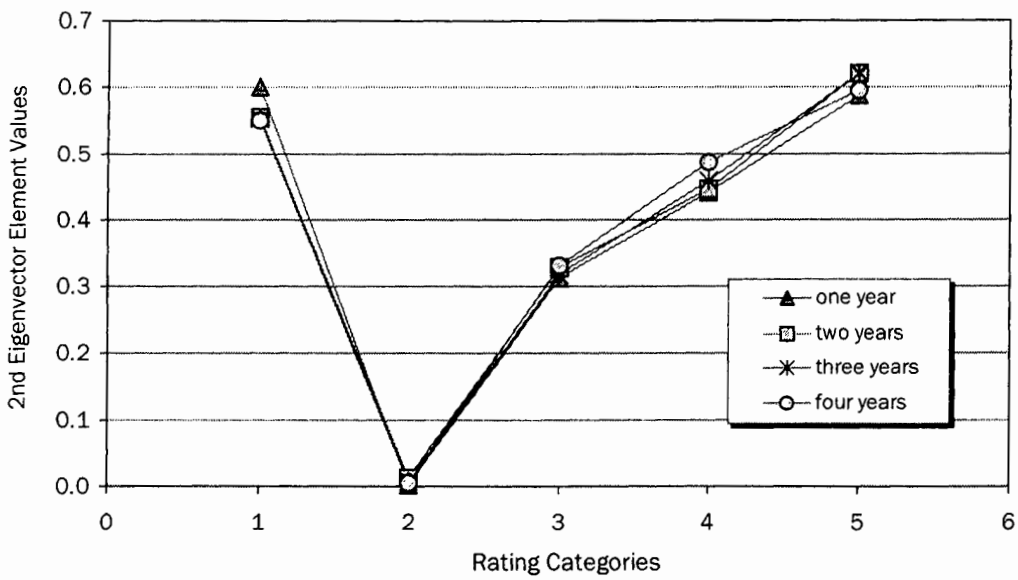

Figure 2. Second Eigenvector Element Values of Matrices for Different Transition Horizons

that each rating migration can be influenced by a previous migration direction (upward, downward, or retention). The statistical formulation of the SPMH model used here is defined as follows:

$$(6)\quad \lambda_{hj}(t) = Y_h(t)\alpha_{hj}\big(t, Z(t)\big),$$

where $\alpha_{hj}(t, Z(t))$ has the multiplicative form

$$(7)\quad \alpha_{hj}\big(t, Z(t)\big) = \alpha_{hj0}(t)\exp\big(\beta_{hj}Z(t)\big).$$

In the above expressions, $\lambda_{hj}(t)$ denotes the migration probability from category h to category j during time t; $Y_h(t)$ denotes an indicator process which takes a value of 1 when the process is in category h and 0 otherwise; $\alpha_{hj0}(t)$ is the time-varying baseline hazard obtained when $Z(t)$ is 0; and the covariate $Z(t)$ is designed to track the last rating change which takes on a value of 1 when such change is the transition process being evaluated (i.e., one of the three possible changes: upward/downward/retention) and a value of 0 otherwise. For example, if the focus of the analysis is only on observations that experienced a previous upgrade in their credit risk classification, then

$$(8)\quad Z(t) = \begin{cases} 1 \text{ if last migration is upward,} \\ 0 \text{ otherwise.} \end{cases}$$

The parameter of interest here is the regression coefficient β_{hj} for each migration possibility.[9] If the coefficient estimates β_{hj} are not significantly different from zero, the Markovian chain assumption will not be rejected. Positive, significant β_{hj} estimates will support path dependence or momentum (reversal) tendencies that are contrary to the Markov chain process assumption.

[9] The maximum-likelihood method was used to estimate β_{hj} by setting $\partial \log L(\beta_{hj})/\partial\beta_{hj} = 0$, where

$$L(\beta_{hj}) = \prod_t \frac{\exp(\beta_{hj}z(t))}{Y_{hj}(t)\exp(\beta_{hj}z(t))}.$$

For additional details, interested readers are referred to Lando and Skodeberg (2002).

In this analysis we use the same three-year groupings used earlier in developing the cohort matrix. However, instead of the 2×1 method, the SPMH framework requires the measurement of two year-to-year (1×1) transitions: movement from t_1 to t_2 and from t_2 to t_3. The direction of the risk rating changes from t_1 to t_2 of every three-year period is used to classify each farm under three categories of previous transitional direction: upgrades, retention, and downgrades.

Matrices are then developed for each of these three categories for every three-year period using risk rating changes during the period t_2 to t_3. These matrices are called conditioned matrices since they are conditional upon previous migration trends. Thus, given 15 three-year periods developed in this data set and three previous migration categories, we produce a total of 45 conditioned matrices. The transition probabilities in these matrices correspond to the variable $\lambda_{hj}(t)$ in equation (6).

Ordinary least squares (OLS) regression techniques are applied to the various runs of equation (6) (using logarithmic transformations of both sides of the equation) as applied to each rating class in t_2 and its migration possibilities in t_3.[10] For example, farms that experienced a rating downgrade during the period t_1 to t_2 and were in class 2 at the end of t_2 would have three "neighboring" migration possibilities

[10] Lando and Skodeberg (2002) performed the SPMH tests only on probable momentum situations. Specifically, they limited their analysis to only succeeding downgrade situations for previous downgrades and consequent upgrades for previous upgrades. This approach, however, excludes other possibilities of trend reversals and the absence of both reversal and momentum tendencies. In our analysis we consider more migration possibilities, although we limited our analysis only to migration to neighboring risk rating classes since most migration activities during the short duration period (year-to-year) are concentrated among these classes anyway. Regression runs for migration activities beyond neighboring classes will utilize much fewer usable observations which will produce results that are not statistically reliable.

at t_3: an upgrade to class 1 (trend reversal), retention in class 2, or a downgrade to class 3 (a case of sustained momentum or path dependence).

Table 2 reports the OLS coefficient estimates obtained with their corresponding standard errors and *p*-values. The results are classified according to the previous migration trend categories and include all "neighboring" migration possibilities given each farm's risk classification at the end of t_2.

The regression results for all possible migration directions/possibilities associated with each rating class in t_2 are actually interdependent. Either an insignificant or a significant negative coefficient for any migration possibility during the period t_2 to t_3 would suggest that a probable significant consequential trend (trend reversal or path dependence) will occur in another migration possibility for that rating class at t_2. The key is to identify this possibility through a significant positive coefficient result. If no such result is obtained for all migration directions associated with a particular rating class at t_2, then no evidence of path dependence is established.

To illustrate, based on the results reported in Table 2, for farms that experienced previous downgrading from t_1 to t_2 and ended up in class 2 at t_2, significant negative coefficient results were obtained for retention (in class 2) and downgrade (to class 3) possibilities. The remaining direction, an upgrade to class 1, however, produced a positive coefficient result. These results indicate that class 2 farms in t_2 which were previously downgraded provide evidence of significant trend reversal. The same result has been obtained for class 3 farms in the previous downgrade category. In the previous rating upgrade category, similar results of significant trend reversal were obtained for farms which were rated as classes 1 and 4 at t_2.

In both previous class downgrade and upgrade categories, only two out of four t_2 rating classes produced significant trend reversal results. Farms in rating classes 4 and 5 in the previous class downgrade category and classes 2 and 3 in the previous class upgrade category did not produce significant positive coefficient results for any t_2 to t_3 migration possibility. Thus, no overwhelming evidence among the previous upgrade and downgrade categories supports the rejection of the Markov chain assumption.

The previous retention cases provide further evidence supporting the non-rejection of the Markov chain assumption. The results for four out of five t_2 rating classes (1 to 4) indicate no significant consequential or sustained retention trends. Only class 5 farms showed a tendency toward significant upgrading tendencies during the last two years of every three-year period.

Developing the Markov Chain Models

The "cohort" transition matrix presented in Table 1 was derived using the conventional, "industry standard" matrix generation method. This approach, however, does not accurately depict actual migration trends due to the omission of certain important information. First, the cohort method is primarily concerned with comparing rating categories at both ends of the time horizon (averaged t_1 to t_2 versus t_3 in the 2×1 method). Any rating class change occurring in-between the endpoints (for instance, transition changes between t_1 and t_2 in the 2×1 method) is ignored. Second, the cohort model only considers direct migration between classes. For example, if direct migrations are recorded only from risk rating class 1 to class 2 and from class 2 to class 3 but none in the direction of class 1 to class 3, the cohort method will yield a zero migration rate for the latter case.

On the other hand, the Markov chain models capture such indirect transition from class 1 to class 3 through the successive downgrades recorded in the

Table 2. Results of Semi-Parametric Multiplicative Hazard Tests

Rating Class at end of Time Period t_2	Rating Class at End of Time Period t_3	Coefficient Estimate	Standard Error	*p*-Value	Evidence of Path Dependence (PD) or Trend Reversal (TR)
PANEL A. Conditional on a Previous Class Rating Downgrade (for the period t_1 to t_2):					
2 →	1	0.64182	0.21937	0.0054	Trend Reversal
	2	-0.28655	0.07214	0.0003	
	3	-0.57744	0.14822	0.0003	
3 →	2	0.48543	0.14165	0.0014	Trend Reversal
	3	-0.46897	0.06500	< 0.0001	
	4	-0.50018	0.17272	0.0060	
4 →	3	0.09780	0.12003	0.4200	No PD/TR
	4	-0.30214	0.15349	0.0561	
	5	-0.86189	0.22402	0.0006	
5 →	4	0.01806	0.14935	0.9049	No PD/TR
	5	-0.52561	0.20272	0.0157	
PANEL B. Conditional on a Previous Class Rating Upgrade (for the period t_1 to t_2):					
1 →	1	-0.39923	0.06170	< 0.0001	Trend Reversal
	2	0.35208	0.15826	0.0340	
2 →	1	-0.92026	0.19554	< 0.0001	No PD/TR
	2	-0.14832	0.08106	0.0741	
	3	0.05729	0.16633	0.7322	
3 →	2	-0.53309	0.14408	0.0006	No PD/TR
	3	0.00854	0.09000	0.9296	
	4	0.20711	0.18678	0.2740	
4 →	3	-0.16916	0.12003	0.1757	Trend Reversal
	4	0.12119	0.18692	0.5206	
	5	0.80925	0.27882	0.0068	
PANEL C. Conditional on a Previous Class Rating Retention (for the period t_1 to t_2):					
1 →	1	0.03544	0.09622	0.7153	No Consequential Trend
	2	-0.48819	0.14527	0.0022	
2 →	1	-0.23210	0.23719	0.3332	No Consequential Trend
	2	0.04826	0.08377	0.5675	
	3	-0.26131	0.16172	0.1134	
3 →	2	-0.22721	0.15603	0.1526	No Consequential Trend
	3	0.13407	0.09389	0.1603	
	4	-0.23162	0.18608	0.2203	
4 →	3	-0.05535	0.12071	0.6490	No Consequential Trend
	4	0.14587	0.16493	0.3819	
	5	-0.08845	0.28397	0.7575	
5 →	4	0.53268	0.13686	0.0008	Significant Upgrading Trend
	5	0.31145	0.25929	0.2409	

above direct migration examples. In this case, the Markov chain approach calculates a nonzero maximum-likelihood estimator for the transition rate for class 1 to class 3. The estimated probability most likely would be a very small, but definitely a nonzero, value. The following sections discuss the two variants of the Markov chain migration approach.

The Time-Homogeneous Markov Chain Model

A distinct feature of the time-homogeneous approach is its nonemphasis on period or time-specific identification. Under this model, only the length of the time interval matters. This feature suggests, for instance, that 2×1 transition rates recorded from 1992 to 1994 will carry the same weight as those calculated for the period 1993 to 1995. This strong assumption on time homogeneity will be revisited and relaxed in the other Markov chain model in the next section.

Following Lando and Skodeberg (2002), we define $\mathbf{P}(t)$ as a $K \times K$ transition matrix of Markov chain processes for a given time horizon (where K represents the number of rating category states) whose ijth element is the probability of migrating from state i to state j in a time period of t. The generator matrix $\mathbf{\Lambda}$ is a $K \times K$ matrix for which

$$(9) \quad \mathbf{P}(t) = \exp(\mathbf{\Lambda} t) \cong \sum_{k=0}^{\infty} \frac{\mathbf{\Lambda}^k t^k}{k!}, \quad t \geq 0,$$

where the exponential function is a matrix exponential, which would be approximated by the infinite summation defined by the most right-hand side expression.

The entries of the generator $\mathbf{\Lambda}$ satisfy

$$(10) \quad \lambda_{ij} \geq 0 \text{ for } i \neq j, \qquad \lambda_{ii} = -\sum_{i \neq j} \lambda_{ij}.$$

The second equation merely guarantees that the sum of the rows of the matrix is equal to one.

The problem of estimating the transition matrix is then transformed to estimating the generator matrix $\mathbf{\Lambda}$. We are left with obtaining the estimates of the entries of $\mathbf{\Lambda}$. The maximum-likelihood estimator of λ_{ij} is expressed as follows:

$$(11) \quad \hat{\lambda}_{ij} = \frac{N_{ij}(T)}{\int_0^T Y_i(s)\, ds},$$

where $N_{ij}(T)$ is the total number of transitions over the period T from credit category i to j and $Y_i(s)$ is the number of observations assigned credit category i at time s. The numerator counts the number of observed transitions from i to j. The denominator, the integral of $Y_i(s)$, effectively collects all observations assigned with category i over the period T. Thus, within the duration of time T, any period spent in a particular rating class will be picked up through the denominator.

To illustrate, suppose a farm spent only a portion of the time period T in transit from class 1 to class 2 before eventually landing in class 3 at the end of T. The portion of time spent in class 2 will be factored into the estimation of the transition rates for classes 1 to 3. In the cohort method, this "transient" migration information is ignored. These indirect transition activities are captured in this model for which positive, though possibly very small, transition rates are estimated.

The upper portion of Table 3 presents the summary matrix for the time-homogeneous approach generated as the average of 15 three-year matrices utilizing the same three-year groupings used for the 2×1 cohort matrices averaged to produce the matrix reported in Table 1. However, in lieu of the discrete-time formula in equation (1), the average transition rates reported in Table 3 are calculated using the maximum-likelihood estimator defined in equation (11) where $T = 3$.

Table 3. Summary Matrices Under the Markov Chain Models, Three-Year Groupings, 1985–2001 (percent)

Period 1 Farm Credit Risk Classes	Period 2 Farm Credit Risk Classes				
	1	2	3	4	5
Time-Homogeneous Markov Chain Model:					
1	76.22	13.50	7.45	2.08	0.75
2	17.10	58.05	15.83	6.64	2.38
3	8.88	15.53	61.01	9.92	4.66
4	6.05	14.59	20.91	52.23	6.23
5	3.11	8.96	22.59	12.74	52.60
Time-Nonhomogeneous Markov Chain Model:					
1	77.89	12.90	6.79	1.92	0.50
2	16.26	59.45	15.66	6.39	2.24
3	7.72	16.20	61.04	9.83	5.20
4	5.27	13.32	22.89	51.15	7.37
5	2.56	9.85	25.99	12.59	49.02

The Time-Nonhomogeneous Markov Chain Model

The time-homogeneity assumption of the previous model is relaxed in this version of the Markov chain transition matrix. Again following Lando and Skodeberg (2002), we define $\mathbf{P}(s, t)$ as the transition probability matrix from time s to t. The ijth element of this matrix corresponds to the transition probability from rating class i in time s to rating class j in time t.

Given a sample of m transitions over the period from s to t, the maximum-likelihood estimator of $\mathbf{P}(s, t)$ could be derived using the following nonparametric product-limit estimator (Klein and Moeschberger, 2003):

$$(12) \quad \hat{\mathbf{P}}(s, t) = \prod_{k=1}^{m} \left(\mathbf{I} + \mathbf{\Delta}\hat{\mathbf{A}}(T_k)\right),$$

where T_k is a jump in the time interval from s to t. The matrix component of the above equation is constructed as follows:

$$(13) \quad \mathbf{\Delta A}(T_k) = \begin{bmatrix} -\frac{\Delta N_{1\cdot}(T_k)}{Y_1(T_k)} & \frac{\Delta N_{12}(T_k)}{Y_1(T_k)} & \frac{\Delta N_{13}(T_k)}{Y_1(T_k)} & \cdots & \frac{\Delta N_{1p}(T_k)}{Y_1(T_k)} \\ \frac{\Delta N_{21}(T_k)}{Y_2(T_k)} & -\frac{\Delta N_{2\cdot}(T_k)}{Y_2(T_k)} & \frac{\Delta N_{23}(T_k)}{Y_2(T_k)} & \cdots & \frac{\Delta N_{2p}(T_k)}{Y_2(T_k)} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \frac{\Delta N_{p1}(T_k)}{Y_p(T_k)} & \frac{\Delta N_{p2}(T_k)}{Y_p(T_k)} & \frac{\Delta N_{p3}(T_k)}{Y_p(T_k)} & \cdots & \frac{\Delta N_{p\cdot}(T_k)}{Y_p(T_k)} \end{bmatrix},$$

where the numerator of each off-diagonal entry, $\Delta N_{ij}(T_k)$, denotes the number of specific transitions moving away from rating class i to some other class (like j) at time T_k. The numerator of the diagonal entry, $\Delta N_{i\cdot}(T_k)$, counts the total number of transitions away from i at time T_k while the denominator, $Y_i(T_k)$, is the number of farms at rating class i right before time T_k. In other words, the diagonal entries of the matrix count, at any time T_k, the fraction of farms in class i migrating away from

that rating class, regardless of which class they migrated to. The off-diagonal entries count the fraction of rating class i farms that migrate away to another specific rating class at time T_k.

Note that the sum of the rows of the matrix $\mathbf{I} + \mathbf{\Delta\hat{A}}(T_k)$ in equation (12) is equal to one. Moreover, when there is only one transition case between time s and t (i.e., $m = 1$), the resulting product-limit estimator [equation (12)] collapses the nonhomogeneous transition matrix into a cohort (discrete-time) matrix. In essence, the time-nonhomogeneous transition matrix is a more time-microscopic (detail-oriented) version of the cohort migration matrix method applied to extremely shorter time intervals.

The lower half of Table 3 presents the summary matrix of average transition rates developed from 15 three-year matrices using the same three-year groupings of the cohort matrix in Table 1 and generated using the $\mathbf{\Delta\hat{A}}(T_k)$ matrix estimator defined in equation (12).

Comparing Cohort and Markov Chain Transition Matrices

In order to determine significant differences among the three matrices presented in Tables 1 and 3, we apply singular value decomposition (SVD) analysis, a metric test based on singular values (Jafry and Schuermann, 2003). Details are presented in the Appendix of the derivation of the SVD statistic, $\overline{S(\tilde{\mathbf{P}})}$, calculated for the cohort (Table 1) and the Markov chain (Table 3) matrices. These values are labeled as

$$\overline{S(\tilde{\mathbf{P}}^d)},\ \overline{S(\tilde{\mathbf{P}}^h)},\ \text{and}\ \overline{S(\tilde{\mathbf{P}}^{nh})},$$

with the superscripts d, h, and nh denoting discrete-time, time-homogeneous, and time-nonhomogeneous methods, respectively. The pairwise differences between the $\overline{S(\tilde{\mathbf{P}})}$ values are calculated as:

$$(14)\quad m_{svd}^{d-h}(\tilde{\mathbf{P}}^d, \tilde{\mathbf{P}}^h) = \overline{S(\tilde{\mathbf{P}}^d)} - \overline{S(\tilde{\mathbf{P}}^h)},$$

$$(15)\quad m_{svd}^{d-nh}(\tilde{\mathbf{P}}^d, \tilde{\mathbf{P}}^{nh}) = \overline{S(\tilde{\mathbf{P}}^d)} - \overline{S(\tilde{\mathbf{P}}^{nh})},$$

$$(16)\quad m_{svd}^{h-nh}(\tilde{\mathbf{P}}^h, \tilde{\mathbf{P}}^{nh}) = \overline{S(\tilde{\mathbf{P}}^h)} - \overline{S(\tilde{\mathbf{P}}^{nh})}.$$

In order to determine significant differences between any pair of matrices under comparison based on the resulting distance metrics, m_{svd}, we use 1,000 bootstrapping samples (random draws with replacement) of 15 observations from the original three-year groupings to calculate 1,000 singular values $m_{svd}^{(k)}$, where $k = 1, \ldots, 1{,}000$. This gives a bootstrap distribution of singular value-based distances from which the confidence interval for the singular value metric can be calculated. Significant differences between any pair of matrices are determined by checking whether zero is within the estimated $1 - \alpha$ confidence interval.

Results

The results of pairwise differences between the $\overline{S(\tilde{\mathbf{P}})}$ values calculated for the summary matrices reported in Tables 1 and 3 indicate the greater relevance of Markov chain models to farm credit risk migration analysis. Using the formulas defined in equations (14)–(16), the mean difference (m_{svd}) between the cohort and time-homogeneous matrices is 0.1924, the mean difference between the cohort and the time-nonhomogeneous matrices is 0.1956, and the smallest mean difference is obtained at 0.0031 between the two Markov chain matrices.

The resulting 95% confidence intervals for each of these differences are (0.1776, 0.2072) for the cohort and time-homogeneous matrices, (0.1700, 0.2211) for the cohort and time-nonhomogeneous matrices, and (-0.0207, 0.0270) for the two Markov chain matrices. Only the last confidence interval includes zero in its range, thereby indicating that the time-homogeneous and nonhomogeneous matrices are not really significantly different from each other at the 0.05 confidence level, while each of them is significantly different from the cohort matrix.

Our results are consistent with the findings obtained by Schuermann and Jafry (2003) for the three methods using S&P bond ratings data for the period 1981–2001. The compelling result is that the mean difference values they obtained [difference (m_{svd}) values of 0.012, 0.014, and 0.002 for comparisons between cohort and time-homogeneous matrices, cohort and time-nonhomogeneous matrices, and time-homogeneous vs. nonhomogeneous matrices, respectively] are much lower than the values we reported here. The disparity of mean difference values obtained for corporate bond ratings and for farm credit risk ratings suggests that farm finance conditions create a greater necessity for making important distinctions between discrete and Markov time models of migration.

Examining the three types of matrices reported in Tables 1 and 3, the Markov chain matrices produced higher average retention rates of 60.02% and 59.71% for the time-homogeneous and nonhomogeneous methods, respectively. The average retention rate for the cohort matrix is only 42.72%. In contrast, corporate bond retention rates range from 70% to 75% for matrices derived under the same three methods (Lando and Skodeberg, 2002).

The more practical and crucial evidence presented here, however, is the capture of "transient" migration events using the Markov chain approaches. In the cohort matrix in Table 1, for example, the average transition probability rates for migrating from class 5 to class 1 and vice versa are 0.25% and 0.11%, respectively. When indirect transitions were captured in the other two models, the transition estimates were higher. The time-homogeneous approach produced a rate of 3.11% for class 5 to class 1 migrations and 0.75% for the reverse migration. The corresponding rates under the time-nonhomogeneous approach were 2.56% and 0.50%, respectively. Moreover, the retention rates in the alternative Markov chain matrices were much higher than their counterparts in the cohort matrix.

In a later section, we revisit these matrices to calculate stress/default probability estimates, which are important portfolio quality indicators that can be obtained from the migration analytical framework.

Replication Using the Farm Lenders' 3 × 1 Method

We validate the relevance of the alternative Markov chain matrices relative to the conventional cohort method by shifting from a 2 × 1 migration measurement approach to the farm lenders' 3 × 1 method. Accordingly, this study's 17-year sample period is regrouped into subset time periods of four consecutive years producing a total of 14 four-year groups, involving an aggregate size of 6,171 farm observations. Under the cohort method, migration rates are recalculated as the transition from the credit class associated with the average of each farm's farm financial measures from t_1 to t_3 to the farm's credit classification in t_4. Migration rates under the Markov chain time-homogeneous approach were calculated using the maximum-likelihood estimator defined in equation (11) where $T = 4$ given the 3 × 1 method used. The time-nonhomogeneous migration matrices were estimated using the $\mathbf{\Delta\hat{A}}(T_k)$ matrix estimator defined in equation (12). The summary matrices for these three methods are presented in Table 4.

As in the previous analysis, we calculate the pairwise differences between the SVD $S(\bar{\mathbf{P}})$ statistics calculated for the three matrices. Results show that the mean difference (m_{svd}) between the cohort and time-homogeneous matrices is 0.1863, the mean difference between the cohort and the time-nonhomogeneous matrices is 0.1925, and the two Markov chain matrices have a mean difference of 0.0062.[11]

[11] The resulting 95% confidence intervals for each of these differences are (0.1677, 0.2048) for the cohort and time-homogeneous matrices, (0.1700, 0.2150) for the cohort and time-nonhomogeneous matrices, and (-0.0149, 0.0273) for the two Markov chain matrices. As in the previous analysis, only the last confidence interval includes zero in its range.

Table 4. Summary Matrices Under the Cohort (farm lenders' 3 × 1 method) and Markov Chain Models, Four-Year Groupings, 1985–2001 (percent)

Period 1 Farm Credit Risk Classes	Period 2 Farm Credit Risk Classes				
	1	2	3	4	5
Cohort (discrete-time) Model:					
1	76.74	15.41	6.52	1.23	0.10
2	28.99	40.23	21.05	8.08	1.66
3	8.67	28.43	38.82	14.94	9.02
4	3.21	18.93	38.83	24.24	14.79
5	0.29	7.84	30.00	28.80	33.07
Time-Homogeneous Markov Chain Model:					
1	74.27	14.10	8.45	2.45	0.73
2	16.81	57.42	17.48	6.78	1.51
3	9.79	14.94	60.10	10.43	4.75
4	6.72	12.80	21.46	53.42	5.61
5	3.77	9.80	23.06	11.48	51.88
Time-Nonhomogeneous Markov Chain Model:					
1	78.03	12.88	6.72	1.89	0.49
2	16.17	59.43	15.71	6.54	2.15
3	7.42	16.35	61.33	9.87	5.03
4	5.19	13.03	23.46	50.94	7.39
5	2.54	10.16	26.61	12.53	48.15

Again, these results remain well above the mean difference values obtained by Schuermann and Jafry (2003) using corporate bond ratings migration. Moreover, the same trends in retention rates and cell-to-cell comparisons between the cohort and Markov chain migration matrices noted when the 2 × 1 method was used for the cohort matrix are also evident in the results for the 3 × 1 method.

The following section wraps up the argument in favor of the alternative Markov chain models through the estimation of loan stress/default probabilities.

Loan Stress/Default Probabilities

Table 5 presents a breakdown of the loan stress/default probability estimates for the 2 × 1 and 3 × 1 measurement methods under the cohort and Markov chain models.[12] These estimates represent the overall frequencies of migrating to (or remaining in) class 5. They are calculated as the weighted averages of the frequencies for class 5 ratings using annual proportion of farm numbers as weights (Barry, Escalante, and Ellinger, 2002; Katchova and Barry, 2005).

The results reported in Table 5 show that probability estimates obtained under the Markov chain model are always above the levels produced by the cohort model for both the 2 × 1 and 3 × 1 methods.[13] For the 2 × 1 method, the "cohort" overall estimate of 5.10% is understated by 0.43% compared to 5.53% estimated using the Markov chain approach. The discrepancy is larger in the 3 × 1 migration method

[12] The time-homogeneous and nonhomogeneous methods produced the same loan default probability estimates since both methods track the same number of farms that migrate either directly or indirectly to class 5.

[13] The differences in unweighted default probability estimates (class 5 transitions divided by total farm number in each time period) are even much larger (ranging from 1 to 3 percentage points) than when weighted estimates were compared.

Table 5. Loan Stress/Default Probability Estimates, Cohort and Markov Chain Models, 1984–2001

Time Period[a]	Number of Farms		2 × 1 Method (%)		3 × 1 Method (%)	
	2 × 1 Method	3 × 1 Method	Cohort	Markov	Cohort	Markov
1	201	174	0.03	0.05	0.21	0.23
2	310	229	0.30	0.31	0.06	0.08
3	345	311	0.11	0.16	0.10	0.11
4	486	404	0.13	0.15	0.96	1.00
5	586	480	0.97	1.05	0.11	0.18
6	656	530	0.17	0.22	0.16	0.28
7	745	570	0.30	0.32	0.47	0.52
8	800	456	0.43	0.47	0.52	0.83
9	566	423	0.16	0.23	0.36	0.70
10	516	406	0.16	0.24	0.49	0.63
11	609	474	0.24	0.24	1.02	0.62
12	675	565	0.35	0.31	0.45	0.49
13	768	610	0.38	0.47	0.41	0.57
14	756	539	0.48	0.53	1.05	1.25
15	732		0.86	0.80		
Total	8,751	6,171	5.07	5.55	6.37	7.49

[a]The time periods were labeled in generic terms to apply to the two measurement methods. The 2 × 1 method uses three-year groupings; hence, time period 1 corresponds to 1985–1987, time period 2 is 1986–1988, and so forth. Similarly, the 3 × 1 method uses four-year groupings; hence, time period 1 corresponds to 1985–1988, time period 2 is 1986–1989, and so forth.

where the Markov chain model produced an overall estimate of 7.47%, which is more than 1% higher than the "cohort" estimate of 6.37%.

For purposes of loan portfolio assessment and financial planning for lenders, more conservative estimates of loan stress/default probability might be preferred to adopt more cautious, prudent lending plans and policies that should provide sufficient cushion against unexpected losses. This stance has greater relevance in a more volatile, uncertain credit environment, much like the challenging lending conditions confronted by all farm lenders.

Concluding Remarks

This study has presented arguments establishing the relevance of Markov chain models in the estimation of credit risk transition probability matrices for farm businesses. The pre-condition of a Markov chain process was validated through an analysis of the eigenvalue/eigenvector of the farm credit risk transition matrix and the semi-parametric multiplicative hazard tests. Our results do not provide strong evidence to reject the Markov property of independence assumption.

This study's empirical evidence supports the application of Markov chain models to farm finance in lieu of cohort models that incorporate the farm lenders' multi-year averaging tendencies in credit risk analysis. The relevance of the Markov chain models in farm credit risk migration could have been diminished if only farm lenders actually employed annual (year-to-year) migration analyses since farm borrowers' financial information is usually reported on an annual basis. In actual practice, however, farm lenders use multi-year averaging techniques in their

credit risk assessment in consideration of the influence of highly volatile business conditions on financial performance in each year. These approaches could possibly lead to the omission of important information on transient changes in the borrowers' credit risk quality during the years between the beginning and end points of any period of time analyzed by the lenders.

In this study, we find more substantial mean differences in singular value decomposition (SVD) are produced between farm credit risk migration matrices developed under the cohort and Markov chain models than when similar comparisons are made in corporate finance literature using bond ratings migration. This finding suggests that the derivation of farm credit risk migration rates under the "cohort" model could result in more costly omission of important indirect, transient changes in farm credit risk ratings. The understatement of transition probability estimates would, in turn, produce lower, if not misleading, indicators of farm loan portfolio quality such as portfolio default probability estimates. For instance, we have shown tendencies to produce lower estimates of loan portfolio stress/default probability under the cohort model than when the Markov chain method is used.

Given the highly variable and largely uncertain farm operating environment where abrupt changes in weather, market, or macroeconomic conditions could influence ad hoc modifications of business plans and decisions, lenders would certainly need more accurate, if not conservative, indicators of loan portfolio quality that need to be factored into their own financial plans and lending policies. This study has shown that Markov chain models of migration could provide a more accurate, reliable representation of farm credit risk migration activities than the conventionally used cohort model. The latter could result in omission of important risk transition information that could be much more costly in the farm finance discipline compared to the area of corporate finance.

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Appendix: Derivation of the Singular Value Decomposition Statistic

The diagonals of any migration matrix represent retention rates or the probability that no cross-state migration has occurred, while off-diagonal elements capture the probabilities of migrating to other classes during a specific period of time. An *identity* matrix (denoted as $\mathbf{I}$) could be treated as a specific migration matrix where only retention cases are observed and cross-state migrations are not realized. Since the migration framework is concerned about activity or dynamics, we then derive the *dynamic* part of migration, called the *mobility matrix* (denoted as $\tilde{\mathbf{P}}$), by subtracting the *identity* matrix from the original matrix (denoted as $\mathbf{P}$), as follows:

$$\text{(A1)} \quad \tilde{\mathbf{P}} = \mathbf{P} - \mathbf{I}.$$

Next, following Schuermann and Jafry (2003), we calculate the singular values [denoted as $S(\tilde{\mathbf{P}})$] of $\tilde{\mathbf{P}}$:

$$\text{(A2)} \quad S(\tilde{\mathbf{P}}) = \sqrt{\text{eig}(\tilde{\mathbf{P}}'\tilde{\mathbf{P}})},$$

where eig(·) is the eigenvalue of the corresponding matrix. Then the average of the singular values of the mobility matrix $\tilde{\mathbf{P}}$ is denoted as $\overline{S(\tilde{\mathbf{P}})}$.

Changes in the Distribution of Farm Wealth in the United States

Ashok K. Mishra, Charles B. Moss, and Kenneth W. Erickson

Abstract

This paper examines the changes in farm sector wealth from 1949 through 2002. The study uses Theil's entropy-based measure of inequality of farm wealth for 10 regions of the United States. The entropy measure is then used to decompose U.S. inequality into within-region and between-region differences. Results show that for the period 1949 to 1993, relative to the number of farms per state, farm wealth in the United States became more equally distributed. However, beginning in 1994, findings suggest inequality in wealth may be increasing.

Key words: farm wealth, inequality, regional decomposition, Theil's inequality

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Since the early work of Ricardo, economists have sought a general explanation of the distribution of personal income and wealth. However, literature on the subject of wealth in agriculture has been scant. Hill (2000) noted the lack of studies on the distribution of wealth, despite the fact that wealth is an important indicator of well-being. In 1965, Boyne explored the linkage between real wealth changes and the welfare implications for asset owners. Boyne also examined the effect of inflation on the distribution of wealth of farm operators.

The adequacy of income and the well-being of the farm business sector have been prominent features of the farm policy debate. Since the early 1950s, the economic well-being of agriculture has varied significantly.[1] Ahearn and El-Osta (1991) compared the wealth distribution of farm businesses in the United States with all U.S. households using the 1988 Farm Cost and Return Survey (FCRS) data from the U.S. Department of Agriculture (USDA) and 1988 U.S. household data from the U.S. Department of Commerce. They found that farm wealth was greater and more equally distributed than all U.S. households. However, Ahearn and El-Osta's study used cross-sectional data collected during the agricultural financial crisis of the mid-1980s, and the cross-sectional nature of the data does not allow for the examination of convergence over time.

[1] The agricultural sector and many individuals realized record levels of income and wealth (Mishra and Sandretto, 2002; Mishra et al., 2002). Additionally, the structure of U.S. agriculture has undergone significant changes since the 1950s (Johnston, 1990; Hallam, 1993).

Skees, Reed, and Pederson (1985) employed simulation techniques to illustrate how relative changes in land prices, returns, and interest rates affect different soybean farms in Illinois. Large farms were found to be more sensitive to changes in farmland values. This sensitivity is higher when the farm owns the farmland, interest rates are low, or the farm has less debt.

A typical measure of farm wealth is average per farm equity. Yet, changes in the national average alone may not reflect significant changes in domestic agriculture. For example, due to a reduction in farm numbers, changes in the distribution of farm size, and the importance of off-farm income over the past six decades, average net worth may not reflect the distribution of farm assets and equity. Consequently, from a policy standpoint, it may be more helpful to examine how shares of total farm business sector wealth are distributed over time and across regions and states.

The present study differs from most earlier studies. Specifically, it uses Theil's measure of inequality to decompose the wealth inequality into regional and within-region inequality over a longer time period (1949–2002).

Informational Measures of Inequality

A variety of measures have been used to measure the dispersion of inequality of economic well-being (e.g., the coefficient of variation, Gini coefficients, and Lorenz curves). This study departs from these formulations, applying instead Theil's measure of inequality. As detailed in this section, our approach has several theoretical advantages and allows for the decomposition of the dispersion into regions. This section first introduces Theil's measure of inequality and describes how the measure can be used to decompose the overall inequality into regional measures of inequality. A discussion of the advantages of this measure is then provided.

Theil (1979) uses his measure of inequality to examine the international dispersion of income over time. In his earlier 1967 work, Theil defines the income inequality as:

$$(1)\quad I(p, q) = -\sum_{i=1}^{N} p_i \ln\left(\frac{p_i}{q_i}\right),$$

where $I(p, q)$ is the measure of inequality (or dispersion), p_i is the income share in region i, and q_i is the share of the population in region i. Theil's measure is based on entropy or mathematical information theory originally proposed by Shannon (1948). Shannon measures the amount of information in a signal as the additive inverse of its entropy ($J(p)$) defined as:

$$(2)\quad J(p) = -\sum_{i=1}^{N} p_i \ln(p_i).$$

As an event becomes certain, $p_i \to 1$, while $p_j \to 0$ for all $j \neq 1$, $J(p) \to 0$, or no information is contained in the signal. Decomposing equation (1), the information inequality is defined as the difference in the information contained in two signals:

$$(3)\quad I(p, q) = -\sum_{i=1}^{N} p_i \ln(q_i) + \sum_{i=1}^{N} p_i \ln(p_i)$$

$$= -\sum_{i=1}^{N} p_i \ln(q_i) - J(p).$$

In this expression,

$$-\sum_{i=1}^{N} p_i \ln(q_i)$$

is the information content regarding income contained in the distribution of population. If the distribution of income is identical to the distribution of population, $p_i \to q_i$ for all i,

$$(4)\quad I(p, q) = -\sum_{i=1}^{N} p_i \ln(q_i) - J(p) \to 0.$$

The measure of inequality then increases as the share of population becomes less similar to the distribution of income, and declines to zero if the two distributions are the same.

in this study we focus on the distribution of farm wealth (equity). The variable p_i is the share of equity[2] in state i defined as the dollars of equity from that state divided by the national amount of farm equity; q_i is the share of farms in a given state, measured as the number of farms in that state divided by the total number of farms in the country.

If the share of the number of farms is close to the share of farm equity, then there is little additional information, and the Theil measure of inequality (TMI) is small. A small inequality in the TMI means the distribution of farm wealth is uniform across states and vice versa. This indicates convergence of farm equity across the nation. Conversely, an increase in the TMI indicates divergence in farm equity across the nation. Further, additivity of the measure allows for the analysis of inequality between regions of the country. This study focuses on the national, regional, and average within-region inequality.

One advantage of Theil's measure of income inequality is its decomposability. Specifically, the share of income and population in region f (P_f and Q_f, respectively) can be defined as follows:

$$(5)\quad P_f = \sum_{i \in f} p_i \text{ and } Q_f = \sum_{i \in f} q_i .$$

The inequality between regions is then defined as

$$(6)\quad I_R = \sum_{f=1}^{F} P_f \ln\left(\frac{P_f}{Q_f}\right),$$

and the inequality within each region is defined as

$$(7)\quad I_f = \sum_{i \in f} \left(\frac{p_i}{P_f}\right) \ln\left(\frac{p_i / P_f}{q_i / Q_f}\right).$$

Based on these definitions,

$$(8)\quad I(p, q) = I_R + \sum_{f=1}^{F} Q_f I_f .$$

[2] The nominal and real informational inequality is identical if inflation is the same across regions.

As previously stated, a plethora of inequality measures have been proposed in the literature, including the coefficient of variation, Lorenz curves, and Gini coefficients. Given this diversity, it behooves the researcher to justify the choice of inequality measure. To justify our application of the Theil inequality measure, we rely on the axiomatic characteristics as developed by Foster (1983) particularly emphasizing the role of decomposability of inequality.

Foster (1983) develops four criteria measuring inequality: (*a*) the Pigou-Dalton transfer principle, (*b*) symmetry, (*c*) homogeneity, and (*d*) the population principle. Taking each in turn, the Pigou-Dalton transfer principle states that the measure of income inequality must increase if income is taken from a poorer individual and given to a richer individual. While this principle would appear fundamental to the concept of equality underlying equity measurement, further support for this principle can be found in Atkinson (1970).

The principles of symmetry and homogeneity denote somewhat different concepts in inequality measurement than those found in consumption and production theory. In the measurement of inequality, the symmetry criterion states that the inequality measure is unchanged when two individuals trade places (or income levels). The homogeneity criterion states that only relative income dispersion matters (i.e., multiplying all incomes by the same proportion does not change the level of inequality).

While several inequality measures meet the first three criteria (the Pigou-Dalton principle, symmetry, and homogeneity), Foster (1983) shows that the Theil measure of inequality alone satisfies the population principle. The population principle states that replicating the sample (i.e., adding a second data set with an identical income distribution) should result in no change in the inequality measure. As Foster demonstrates, the decomposability of the Theil measure is a

requirement to meet the population principle.

Hence, given our interest in the inequality of farm wealth within various regions, the most appropriate measure of inequality is the TMI. Ideally, one would prefer to assess income or wealth inequality at the micro level; however, one of the key dimensions of farm production sector structural change is the distribution of farms and farm business wealth over time. Unlike the micro-level data time series, state-level data (1949–2002) on farm wealth and associated farm structure are readily available and come from comparable sources which are consistent over the time period. Therefore, state-level data allow us to examine wealth inequality along with structural changes over a long time period.

Data

To measure the dispersion of farm wealth, this study uses the estimated state-level balance sheets published by the U.S. Department of Agriculture, Economic Research Service (USDA/ERS, 2004).[3] The estimated balance sheet data include assets, debt, and equity (defined as farm assets minus farm debts).

Assets and debt for both operators and landlords are included, but the data exclude the household assets and debts of farm operators. In this data set, farm assets consist of real estate (land and buildings) and non-real estate (livestock and poultry, machinery and equipment, crop inventories, financial assets, and purchased inputs). Farmland values have dominated the agricultural balance sheet, accounting for 70% of all agricultural assets from 1960 through 2002.

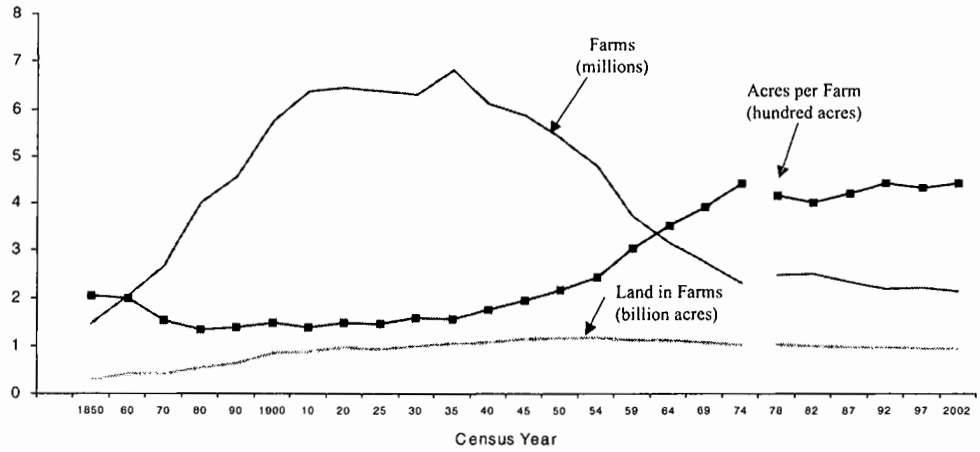
Farm debt includes real estate and non-real estate debts incurred through loans which are classified depending on the asset (real or non-real) used to secure the loan. If the loan is secured by farm real estate, the debt is classified as real estate debt regardless of how the proceeds of the loan are used. Because Commodity Credit Corporation (CCC) loans were historically used to support prices, CCC loans were excluded from total farm debt.

Structure and Wealth of American Farm Businesses

Before proceeding to a discussion of the wealth position and inequality in farm wealth of farm operators, it is necessary to point out some basic facts, such as number of farms, size, and distribution of farms, which have a direct role in the way we calculate Theil's measure of inequality (TMI). Ninety-eight percent of U.S. farms are family farms and, according to the *Census of Agriculture*, the number of U.S. farms fell sharply until the early 1970s after peaking at about 6.8 million in 1935 (Figure 1). Falling farm numbers during this period reflected growing productivity in agriculture and increased nonfarm employment opportunities (Mishra and Sandretto, 2002). The decline in farm numbers slowed in the 1980s and nearly stopped in the 1990s. By 2002, about 2.1 million farms remained. Figure 1 shows farms averaged 441 acres in 2002 versus 155 acres in 1935.

The trend in the number of farms differs by acreage. Acres are generally used to indicate farm size. The number of farms with at least 500 acres increased steadily from 1880 through the 1960s, before stabilizing at 350,000 to 370,000 farms (Figure 2). Farms with 1–49 acres declined from their peak of 2.7 million in 1935 to

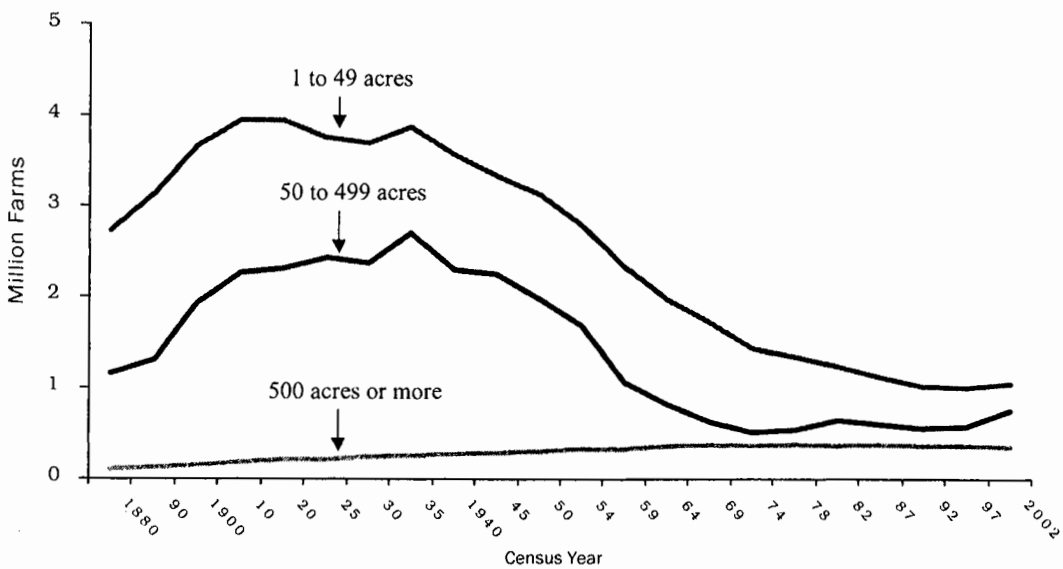
[3] The regions used in this study are the 10 regional divisions of states used by the USDA/ERS, as follows: the Northeast (Connecticut, Delaware, Maine, Massachusetts, Maryland, New Hampshire, New Jersey, New York, Pennsylvania, Rhode Island, and Vermont); the Lake States (Michigan, Minnesota, and Wisconsin); the Corn Belt (Illinois, Indiana, Iowa, Missouri, and Ohio); the Northern Plains (Kansas, Nebraska, North Dakota, and South Dakota); Appalachia (Kentucky, North Carolina, Tennessee, Virginia, and West Virginia); the Southeast (Alabama, Florida, Georgia, and South Carolina); the Delta (Arkansas, Louisiana, and Mississippi); the Southern Plains (Oklahoma and Texas); the Mountain States (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming); and the Pacific States (California, Oregon, and Washington).



Source: Compiled from *Census of Agriculture* data (USDA/Economic Research Service).

Notes: The break in the lines after 1974 reflects the introduction of an adjustment to estimates of the farm count and land in farms. Beginning in 1978, the data are adjusted to compensate for under-coverage by the *Census of Agriculture.* (For additional information, see Allen, 2004.)

Figure 1. Farms, Land in Farms, and Average Acres per Farm (1850–2002)



Source: Compiled from *Census of Agriculture* data (USDA/Economic Research Service).

Figure 2. Distribution of Farms by Acreage Class (1880–2002)

about half a million in 1974. After 1974, these farms have numbered between 540,000 and 640,000. In contrast, the numbers of farms with 50–499 acres declined continuously from 3.9 million in 1935 to about a million farms in 1997. As a result of these changes, farms with fewer than 50 acres and farms with 500 acres or more have increased their share of total farms since 1974, while the share of midsize farms has declined.

On the other hand, the level of farm sales is arguably a better indicator of farm size than number of acres. It measures farm production for the market in dollars, in comparison to the level of one input (land). When using sales to measure trends in farm size over time, it is important to adjust for changes in agricultural prices (computation is done using longitudinal *Census of Agriculture* files), which change revenue without any changes in the physical volume of production. Large farms (sales of at least $250,000) grew consistently over the 1982–1997 period from 104,000 in 1982 to 157,000 in 1997; however, their number decreased slightly (less than 3%) over the 1997–2002 period, with much of this reduction coming from decreases (about 4.4%) in the $250,000–$999,999 sales group (Table 1). The number of farms in the $10,000–$49,999 sales group show a downward trend—about 11% decrease during 1992–1997 and about 7% during 1997–2002. Most of the increase from the 1982–2002 period occurred in large farms with sales of $1 million or more.

As depicted in Figure 3, average equity per farm increased from $18,000 in 1950 to a peak of $343,000 in 1980. Several factors contributed to this increase. Over this period, the average farm size increased from 235 acres to 425 acres. In addition, the value of farmland increased from $10,000 to $300,000 per farm. After 1980, the average equity per farm declined to $253,000 in 1986 as the farm sector in the United States experienced a period of financial stress. Since 1986, however, the average equity per farm increased to $514,000 as farmers reduced their debt level and asset values increased substantially.

These aggregate changes mask regional variations in equity growth. Figure 4 presents the average equity per farm for the ERS Northern Plains, Corn Belt, and Lake States regions. The equity per farm for these regions is similar to the aggregate patterns depicted in Figure 3. However, farms in these regions may exhibit greater variation because they are generally larger and more specialized.

As shown in Figure 5, farms in the Northeast and Appalachia were largely unaffected by the farm financial crisis of the 1980s, unlike farms in the Northern Plains, Corn Belt, and Lake States. Both of these regions show a more consistent upward trend in equity per farm. The difference may be attributed to the fact that farms in the Northeast and Appalachia are generally smaller and better diversified (Gardner, 2002; Tauer and Seleka, 1994; Sommer and Hines, 1991; Blandford, 1999) than farms in the Northern Plains, Corn Belt, and Lake States. Figure 6 indicates that equity values in the Southern Plains did not recover as quickly from the financial crisis of the 1980s, while the recovery in the equity value per farm started earlier in the Southeast region.

Results

Changes in the inequality of farm wealth over time must be viewed through the prism of significant changes in structure that have occurred in U.S. agriculture since World War II (Erickson et al., 1991). These structural changes have taken place in combination with changes in products/commodities produced and methods of production (e.g., machinery, equipment, buildings, and labor). Cochrane (1979) provides a brief discussion of the factors that have contributed to structural changes in U.S. agriculture. For example, a dollar of equity in the 1950s may represent a considerably different set of assets and debt instruments than in the 1990s.

Table 1. Number of Farms by Constant-Dollar Sales Class (2002 $): 1982, 1987, 1992, 1997, and 2002

Constant-Dollar Sales Class (2002 $)	Census Year					Change (percent)			
	1982	1987	1992	1997	2002	1982 to 1987	1987 to 1992	1992 to 1997	1997 to 2002
Total Farms	2,240,976	2,087,759	1,925,300	1,911,859	2,128,982	-6.8	-7.8	-0.7	11.36
Sales between $10,000 and $49,999:	592,328	557,006	502,229	444,745	414,063	-6.0	-9.8	-11.4	-6.90
$10,000 to $19,999	262,616	256,448	234,770	212,120	197,967	-2.3	-8.5	-9.6	-6.67
$20,000 to $24,999	82,080	78,078	68,709	61,920	58,190	-4.9	-12.0	-9.9	-6.02
$25,000 to $39,999	167,003	151,212	137,341	117,196	109,310	-9.5	-9.2	-14.7	-6.02
$40,000 to $49,999	80,629	71,268	61,409	53,509	48,596	-11.6	-13.8	-12.9	-9.18
Sales between $50,000 and $99,999:	253,069	217,479	186,937	158,160	140,479	-14.1	-14.0	-15.4	-11.18
Sales between $100,000 and $249,999:	239,923	228,514	216,334	189,417	159,052	-4.8	-5.3	-12.4	-16.03
Sales of $250,000 or more (large farms):	104,146	118,014	139,958	156,571	152,336	13.3	18.6	11.9	-2.70
$250,000 to $499,999	70,173	76,764	86,968	87,777	81,694	9.4	13.3	0.9	-6.93
$500,000 to $999,999	22,914	27,151	34,911	42,860	41,969	18.5	28.6	22.8	-2.03
$1,000,000 to $2,499,999	8,090	10,250	13,139	19,069	20,724	26.7	28.2	45.1	8.68
$2,500,000 to $4,999,999	1,724	2,213	2,919	4,066	4,611	28.4	31.9	39.3	13.40
$5,000,000 or more	1,245	1,636	2,021	2,799	3,338	31.4	23.5	38.5	19.26

Source: Longitudinal files, *Census of Agriculture*, 1982, 1987, 1992, 1997, and 2002 (USDA/Economic Research Service).

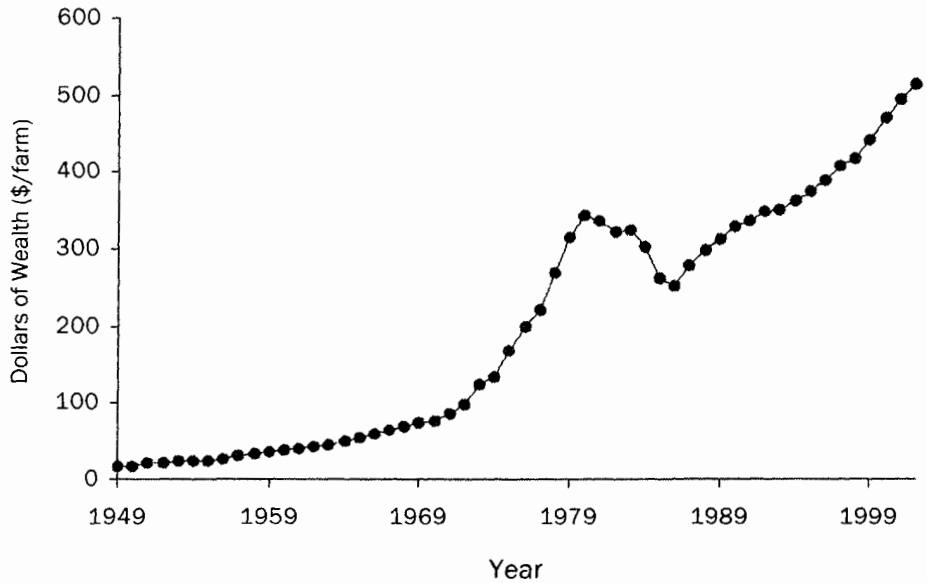


Figure 3. Average Equity per U.S. Farm (1949–2002)

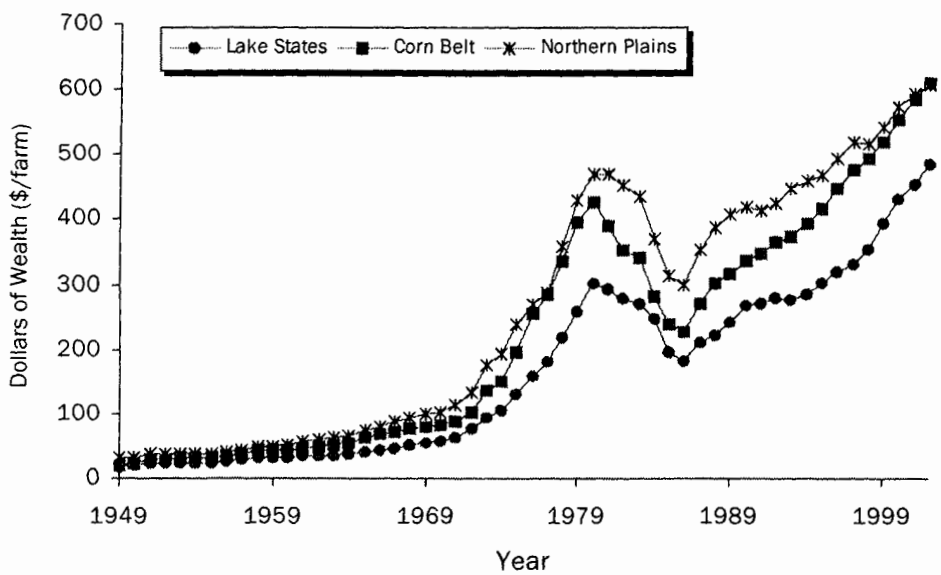


Figure 4. Average Equity per Farm for Lake States, Corn Belt, and Northern Plains (1949–2002)

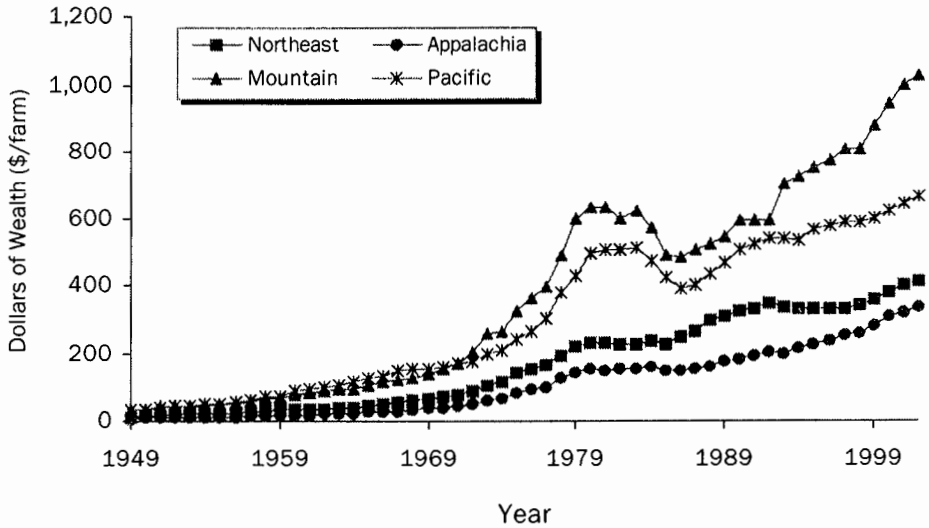


Figure 5. Average Equity per Farm for the Northeast, Appalachia, Mountain, and Pacific Regions (1949–2002)

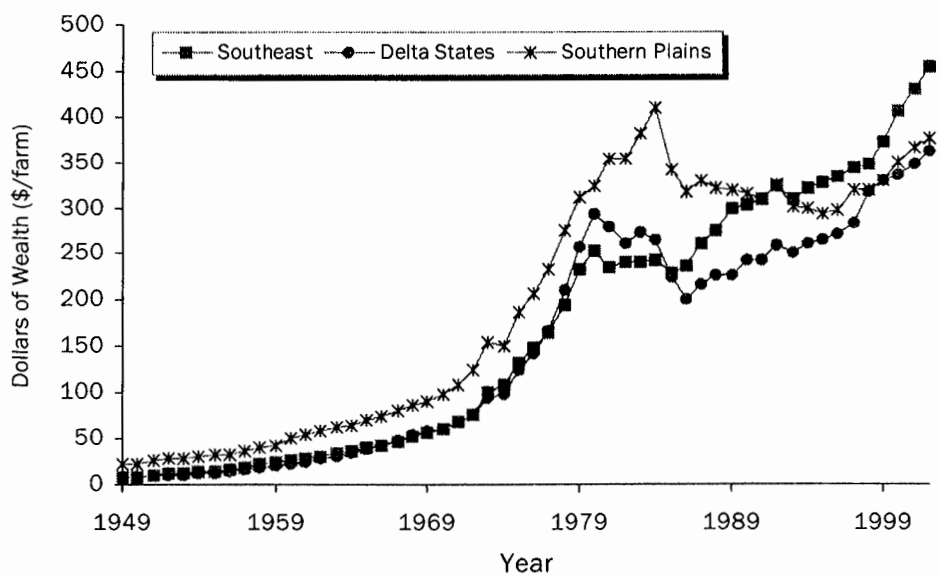


Figure 6. Average Equity per Farm for the Southeast, Delta States, and Southern Plains (1949–2002)

Furthermore, the number and distribution of farms by state and region have changed significantly over the study period. These structural changes must be considered in analyzing the changes in within- and between-region inequalities (Hallam, 1993).

In general, the results reveal that the distribution of farm equity has changed significantly from 1949 through 2002. As observed from Figure 7, the equity per farm has converged over time. The most dramatic convergence occurred between 1950 and 1975. During this period farm incomes increased steadily, particularly in the areas with commodity price supports such as grains and dairy (Gardner, 2002). Growing farm exports and accommodating farm credit policies likewise may have contributed to the convergence in farm equity. An increasing number of small farms with minimal debt and increased off-farm incomes also brought outside equity into agriculture.

Moreover, as one reviewer noted, during the last 30 years the federal definition of a farm has not effectively changed. The highest levels of national inequality (0.185) as measured by TMI were observed in 1949. Over the next four decades the inequality measure (TMI) of farm wealth fell to 0.076 in 1992, indicating a more uniform distribution of farm wealth. Results show a 59% reduction in farm wealth inequality at the national level. However, the total inequality increased slightly, about 8%, from 0.106 in 1993 to 0.114 in 2002, indicating a modest rise in wealth inequality.

As developed above, decomposing the overall inequality into dispersion across regions and the average dispersion within each region can provide additional insights. Variations across states within a region tend to reflect microeconomic conditions because states within each region tend to be rather homogeneous. However, variations across regions tend to reflect macroeconomic differences such as changes in farm structure (i.e., changes in the distribution of farm size or methods of production). Figure 7 presents the total inequality [$I(p, q)$ in equation (8)], the inequality across regions [I_R in equations (6) and (8)], and the average inequality within each region,

$$\bar{I}_f = \sum_{f=1}^{F} P_f I_f,$$

where I_f is defined in equation (7).

Convergence Across Regions

Overall, the inequality across regions accounted for a 93% reduction in the total inequality in farm wealth between 1949 and 1992. The inequality across regions (I_R) decreased steadily from a high of 0.143 in 1949 to 0.042 in 1992 (Figure 7), representing a 71% decrease in farm wealth inequality over four decades. During this period, agriculture in the United States went through significant structural changes. The number of farms declined and the average size of farms increased through consolidation. These changes were partly due to a more open and global economy, greater capital and labor mobility, and the deregulation of capital markets. The expansion/consolidation of agriculture resulted in a more even distribution of wealth across the states relative to the number of farms in each state.

However, the ratio of the across-regions measure to overall inequality decreased from 54% in 1995 to 45% in 2002. This finding suggests that since 1995, the regions have become more similar, or that macroeconomic and structural differences in agriculture have declined.

Changes in Average Inequality Within Regions

The decline in the wealth inequality can be partially attributed to a steady reduction in the average within-region inequality over time (Figure 7). The average within-region inequality ($\bar{I}_f$) declined from 0.060 in 1963 to 0.035 in 1992. Consequently, of the 0.109 reduction in the overall inequality in wealth, 0.007 or 7% was due to the reduction in equality within regions.

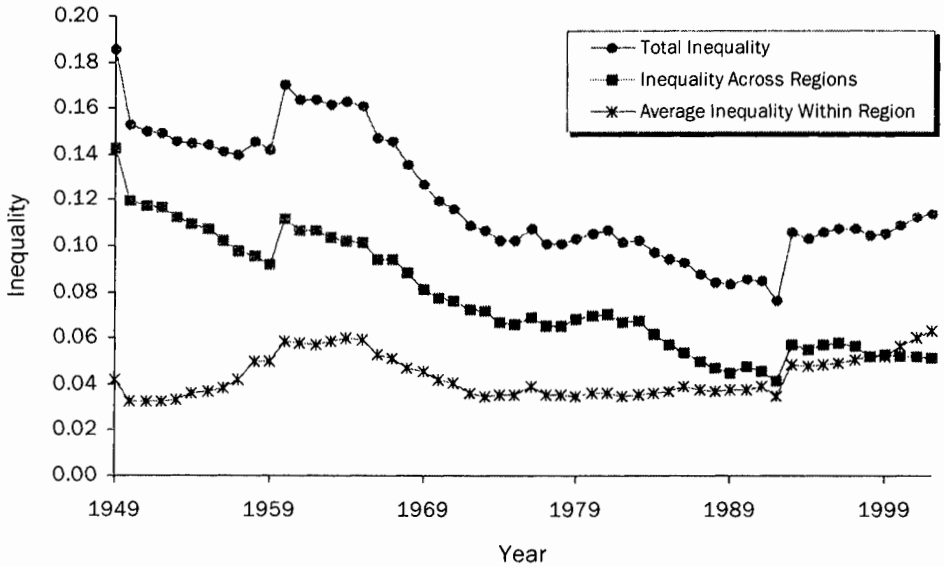


Figure 7. Overall, Average Within, and Regional Inequality for the United States (1949–2002)

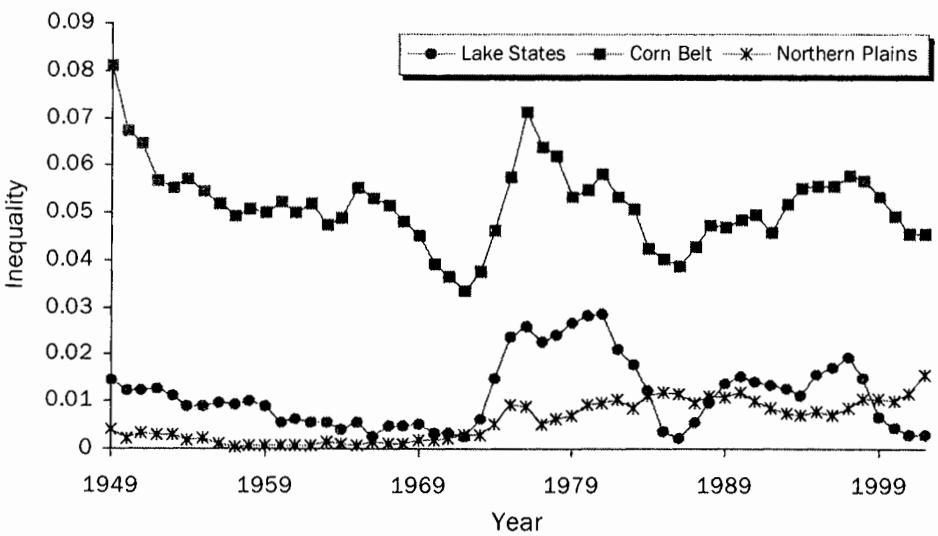


Figure 8. Inequality Within Lake States, Corn Belt, and Northern Plains (1949–2002)

Changes in Within-Region Inequality

The within-region inequality of farm equity [I_f in equation (7)] for each of the 10 ERS regions is presented in Figures 8, 9, and 10. Figure 8 presents the average within-region inequality for the major farming regions (i.e., the Lake States, Corn Belt, and the Northern Plains). For 1949, the Corn Belt displayed the largest level of inequality between states (0.081). The inequality in the Corn Belt region then trended downward for the next two decades. In 1972, the inequality of farm wealth reached its lowest point for the Corn Belt region (0.033). The inequality of farm wealth then began to increase for this region. One explanation for this increasing inequality could be the expansion and consolidation phase observed during this time period across the Corn Belt (Gardner, 2002). The inequality in the Corn Belt continued to increase, reaching its highest level in 1976 of 0.071. Following 1976, the inequality in farm wealth continued to decline until 1986, which coincidentally was the trough of the agricultural financial crisis.

In general, the Lake States region shows the same pattern of inequality observed in the Corn Belt, but at a much lower level. The Northern Plains show a brief period of increase corresponding with the 1976 increase observed in both the Lake States and the Corn Belt, but the inequality in the Northern Plains exhibits less response to the financial crisis of the 1980s. This finding is consistent with the fact that between 1950 and 1970, the region lost farms rapidly and after 1970 the rate of decline moderated, but farm numbers continued to fall until the 1990s. At the same time, farms acquired capital to expand the business and improve farm machinery and implements (Gardner, 2002). The empirical evidence for both the Corn Belt and Lake States supports a linkage between the expansion of commercial or large-scale farms leading to a consolidation within the farm sector. As the farm sector consolidates, the inequality of equity increases. However, when the commercial farms contract (as seen in the period of financial crisis of the 1980s), the overall inequality of equity declines. This cycle of expansion and contraction in the inequality of farm wealth suggests the structure of agriculture is less responsive for some states in the region.

From 1950 through 1963, the inequality in farm wealth for the states in the Southern Plains and Delta States increased more than for any other region (Figure 9). This increase may have resulted from the growth in larger farms in these regions over that same time period. The inequality in the Southern Plains increased from 2.83×10^{4} in 1980 to 0.0132 in 2001. This resurgence was primarily the result of the increased share of equity in Oklahoma.

Figure 9 also presents the inequality results for the Southeast region. The inequality in equity increased from 0.067 to 0.226 in the Southeast region between 1950 and 1960, and then declined to 0.108 in 1971. After 1971, the inequality in the Southeast was around 0.100 until 1987 (post-farm financial crisis), then declining to its minimum of 0.027 in 1999, indicating a more uniform distribution of farm wealth among farms in the Southeast region. Recent data show that the number of small farms and poultry contracting have increased in the Delta States and the Southeast region. Furthermore, farms in the Southeast region have a substantial amount of off-farm income. This off-farm income may supply additional equity capital to farmers for the purchase of new capital investments, leading to a more uniform distribution of farm wealth.

Figure 10 graphs the inequality in farmer wealth for the Northeast, Appalachia, Mountain, and Pacific regions. The Northeast and Appalachia regions show the most inequality over the sample. Farms in these regions tend to be small and agriculture labor intensive. As Blandford (1999) points out, agriculture in the Northeast is relatively diversified; yet dairy, fruit, and vegetables remain dominant enterprises. Beginning in 1997, the inequality has been increasing for the

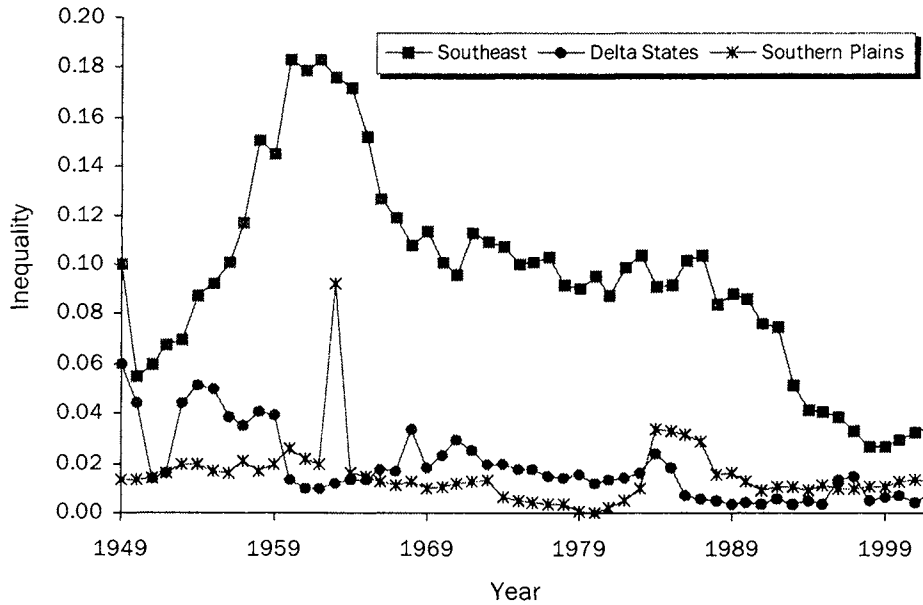


Figure 9. Inequality Within the Southeast, Delta States, and the Southern Plains (1949–2002)

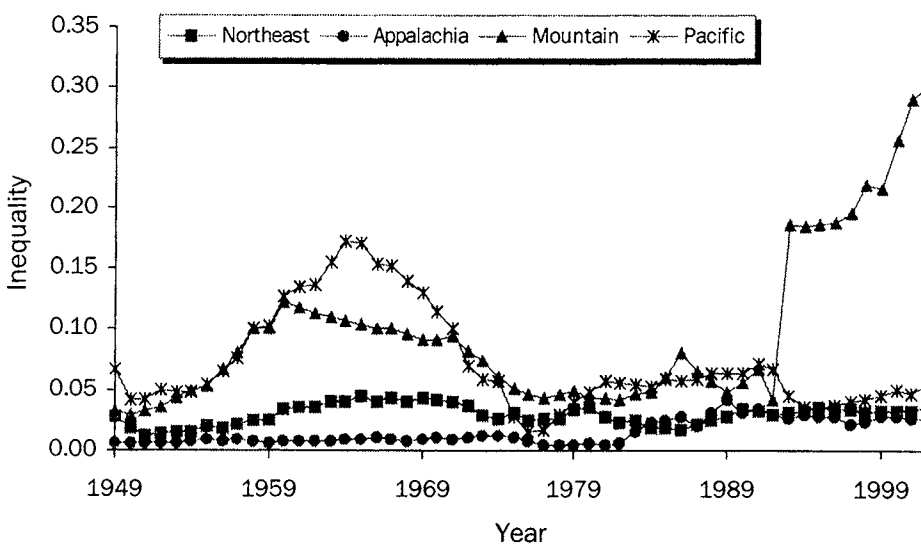


Figure 10. Inequality Within the Northeast, Appalachia, Mountain, and Pacific Regions (1949–2002)

Northeast. This rise could be partly due to the growth in farmland values as a result of urban pressure (Moss et al., 2002). This growth in farmland values provides unrealized capital gains. In addition, increased off-farm income from suburban employment opportunities may have contributed to the growth in farm equity.

The Pacific and Mountain regions show a very different pattern over time (Figure 10). The inequality in the Pacific region increased from 0.042 in 1950 to a high of 0.172 in 1964. The inequality then declined to 0.016 in 1976. Farms in California, Oregon, and Washington saw their share of equity rise because of increased foreign and domestic demand for grains, fruits, and vegetables. From 1977–1992, California's share of equity in the region rose steadily, reflecting that state's expanding agricultural sector.

The Mountain States show a dramatic jump in inequality starting in 1992—possibly the result of a reclassification of Native American Lands in 1992. Specifically, in 1992 the National Agricultural Statistics Service (NASS) readjusted the value of agricultural land in Arizona, Nevada, Utah, and New Mexico by excluding the value[4] of Native American lands. NASS justified this exclusion because Native American lands are not traded, and hence full market value is not realized. Farmland values in these states jumped from $310 per acre in 1991 to $810 in 1992. As a result, the inequality in equity for the Mountain region as a whole increased from 0.041 in 1992 to 0.185 in 1993, and to 0.302 in 2002.

Summary and Conclusions

This study analyzed the change in the distribution of farm wealth between 1949 and 2002 using Theil's measure of inequality. The period of analysis contains several periods of significant structural changes and policy regimens affecting production agriculture in the United States. We use Theil's measure because it is consistent and has desirable properties compared to other measures of inequality such as Lorenz curves, Gini coefficients, or the coefficient of variation. Most of these desirable properties result from the decomposability of the Theil measure.

Between 1949 and 2002, the economic well-being of agriculture has varied significantly. Changes in aggregate demand, farm policies (including production controls, subsidized credit, and income transfers), and macroeconomic factors such as interest rates and inflation have directly affected the level of farm assets and debts. These changes in assets and debt imply changes in farmer wealth. In the 1950s and early part of the 1960s, farmers benefited from increasing prices and incomes. The 1970s saw unprecedented growth in foreign and domestic demand for farm products. However, agriculture also recorded significant losses during the farm financial crisis of the 1980s and a major reduction in farm numbers in the decade and a half that followed.

Our results indicate that the largest inequality in farm equity occurred in the 1950s and early 1960s. The largest convergence in farm equity took place from 1960 through 1992. Much of this decline likely can be attributed to a reduction in the number of farms and concentration of production within a few remaining farms. Starting in 1993, there was a small increase in the overall inequality of wealth, both at the aggregate and regional levels. From 1993 through 1999, the farm sector in the United States recorded some of the highest historical incomes, while government support payments were reduced for many commodities. In addition, recent years have seen an increase in the number of small farms with little or no debt and increased off-farm income. Both of these factors have contributed to the stability of the U.S. agricultural sector.

[4] Value of land and buildings, as defined by the National Agricultural Statistics Service, is the value at which all land and buildings can be sold under current market conditions (USDA/NASS, 1999).

The decomposition of the inequality of farm wealth is helpful in explaining the extent to which microeconomic and macroeconomic factors have occurred over time. Changes in the inequality of farm equity across regions provide evidence on changes in macroeconomic factors such as farm structure and agricultural policies, while changes in the inequality within a region offer evidence of microeconomic changes. Farm-level data (longitudinal in nature) may be useful in further understanding these relative changes because these data would provide information on farms by farm size, tenure arrangement, and other structural characteristics.

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Analysis of Rainfall Derivatives Using Daily Precipitation Models: Opportunities and Pitfalls

Martin Odening, Oliver Musshoff, and Wei Xu

Abstract

This study examines rainfall variability and its implications for wheat production risk in northeast Germany. The hedging effectiveness of rainfall options and the role of geographical basis risk are analyzed using a daily precipitation model. Simpler pricing methods such as the burn analysis and the index value simulation serve as benchmarks for comparison. It is found that the choice of statistical approach may lead to considerable differences in the estimation results. Daily precipitation models should be used with some caution in the context of derivative pricing because they tend to underestimate rainfall variability. This is unexpected, because daily simulation models are usually preferred in the context of temperature-based weather indexes.

Key words: hedging effectiveness, precipitation modeling, weather derivatives

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Weather, though an important production factor in agriculture, can hardly be controlled. In fact, weather risks are a major source of uncertainty in crop production. Traditionally, producers have tried to compensate for the negative economic consequences of bad weather events by purchasing insurance. However, weather derivatives, a new class of financial instruments that permit the trade of weather-related risks, emerged in the mid-1990s. These instruments include futures, options, and swaps, all of which are traded over the counter and on formal exchanges such as the Chicago Mercantile Exchange (CME). Common underlying weather variables are temperature, rainfall, or wind.

The advantage of weather derivatives is that their payoffs are determined in a transparent manner and with low transaction costs. Moreover, they are not affected by moral hazard or adverse selection, which can be serious problems for insurance companies. Yet, considerable risk may remain with the producer when using weather derivatives (*a*) because individual yield variations are not, in general, completely correlated with the relevant weather variable, and (*b*) because of geographical basis risk—i.e., the difference between the weather index at a reference point and at a specific farm location.

To date, it has been unclear if weather derivatives would permeate agriculture. But the literature increasingly deals with the question of whether weather derivatives can also play a role as agribusiness risk management tools (e.g.,

Turvey, 2001, 2005; Richards, Manfredo, and Sanders, 2004; van Asseldonk and Oude Lansink, 2003).

Analyzing the hedging effectiveness of weather derivatives requires three interrelated problem areas to be solved: first, the statistical modeling of relevant weather variables; second, quantifying the relationship between weather variables and production; and third, developing a theoretically consistent pricing model. This paper focuses on the availability of a reliable statistical model of the weather variable, which is important because it facilitates the quantification and prediction of the weather risk. Moreover, it is a necessary ingredient for calculating the price of the weather derivative, i.e., insurance costs. Substantial research exists with regard to the statistical modeling of temperature-related derivatives (e.g., Campbell and Diebold, 2005; Jewson and Brix, 2005), but few papers deal with statistical models of rainfall derivatives, despite the importance of rainfall for agricultural production.

Obviously there are significant differences between analyzing rainfall and temperature. Rainfall is a binary event and evolves much more erratically than temperature changes. Further, the correlation between rainfall amounts at adjacent locations is relatively low. Most of the existing applications of rainfall insurance prefer to estimate the probability law of the rainfall index directly, assuming an appropriate distribution function (Stoppa and Hess, 2003; Skees et al., 2001). Turvey (1999) compares the results of an empirical and a normal distribution. Cao, Li, and Wei (2004) were the first to suggest calculating the derivative payoff from a rather subtle stochastic process of daily rainfall.

This paper has two objectives. The first is the development, estimation, and comparison of different precipitation models. Comparing these models reveals their strengths and weaknesses and facilitates the assessment of their usefulness for analyzing rainfall-based weather derivatives or insurance in agriculture. In particular, we wish to investigate whether the use of daily simulation models can actually improve the pricing of rainfall derivatives, as is the case for temperature-related derivatives. The second objective is to examine the role of basis risk for the hedging effectiveness of rainfall derivatives. Our focus lies on the quantification of geographical basis risk by means of a de-correlation analysis. The precipitation model and the de-correlation analysis are applied to a case study that considers wheat production in Germany.

The remainder of the paper is structured as follows. First, the theoretical background of weather derivatives is briefly reviewed. Next, alternatives of index modeling are discussed. A daily precipitation model is then presented, followed by an empirical application. Using rainfall data from the Brandenburg region of Germany, put options on two rainfall indexes are priced with different methods, and the effect of wheat producers' exposure to risk is examined. The paper ends with conclusions related to the proposed statistical approach.

Valuation of Weather Derivatives

Pricing Weather Derivatives

Financial theory asserts that the price of a contingent claim, F, which depends on stochastic variable I and expires at time T, can be calculated according to (Neftci, 1996, p. 297):

$$(1) \quad F = \tilde{E}[W(I)] * \exp(-r * T),$$

where $W(I)$ denotes the payoff of the derivative at expiration, and r is the risk-free interest rate. The variable E represents expectation, conditional on the information available at present, and the tilde (~) indicates that the expectation of the derivative payoff is calculated by

means of risk-neutral probabilities instead of real-world probabilities. The use of risk-neutral probabilities ensures the derivative price is arbitrage free. This is a desirable property when the derivative is traded before it expires.

To illustrate this concept, consider variable I, which follows a geometric Brownian motion with an expected growth rate α and volatility σ. To calculate the price of a derivative in a risk-neutral world, the actual growth rate α must be reduced by a risk premium ($\lambda * \sigma$) while volatility remains unchanged. The variable λ is known as the market price of risk for I. Hull (2006, p. 590) proves that if I is a traded asset, the market price of risk is given by $\lambda = (\alpha - r)/\sigma$. Inserting this into the above expression for the risk premium shows that the risk-adjusted discount rate is simply the risk-free interest rate r. This fact is well known from the Black-Scholes model.

However, the direct application of no-arbitrage models to weather derivatives is impractical since weather cannot be traded. If I is a weather index, it is not possible to construct a risk-free hedge portfolio consisting of I and the derivative F, and hence the price of the derivative must account for the market price of weather risk. Weather derivatives are typical examples of an incomplete market. Unfortunately, there is no unique way to "risk-neutralize" the objective (real-world) probability distribution of the underlying I in the case of an incomplete market. Accordingly, many arbitrage-free prices for the derivative exist (Benth, 2004, p. 88).

Various proposals for treating this problem can be found in the literature. Alaton, Djehiche, and Stillberger (2002) determine the market price for weather risk to be an implicit parameter such that the theoretical pricing model matches the observable market prices for some contracts. Of course, this approach is only practical if a market already exists for weather derivatives. Cao and Wei (2003) and Richards, Manfredo, and Sanders (2004) apply an extended version of Lucas' (1978) equilibrium pricing model where direct estimation of the market price of weather risk is avoided. Instead, pricing is based on the stochastic processes of the weather index and an aggregated dividend. Moreover, an assumption about the utility function of a representative investor is required.

Turvey (2005) refers to the capital asset pricing model in order to estimate the market price of risk. From the CAPM we have:

$$(2) \quad \mu = r + (\mu_M - r) * \rho * \frac{\sigma}{\sigma_M},$$

where μ and σ are the expected value and the standard deviation of the returns of an asset, respectively. Variables μ_M and σ_M denote the corresponding values of the market portfolio, and ρ measures the correlation between the asset and the market portfolio. Combining (2) with the definition $\lambda = (\mu - r)/\sigma$ provides an estimable relation for λ:

$$(3) \quad \lambda = \rho * \frac{(\mu_M - r)}{\sigma_M}.$$

In the subsequent application, we will argue in accordance with Hull (2006, p. 552) that rainfall indexes have no (or a negligible) correlation with stock market returns, i.e., rainfall variability is not a systematic risk. In that case, the market price of risk is zero, and no correction with the distribution of the weather index is necessary. This means the expectation in (1) can be calculated with real-world probabilities.

Determining Hedging Effectiveness

Agricultural producers rarely evaluate a weather derivative via its contribution to a well-diversified investment portfolio. Rather, they are interested in knowing if and to what extent the existing yield risk can be eliminated by holding this security. The risk reduction that can be attributed to weather insurance is measured by

comparing the revenue distribution of a production activity or a whole farm with and without having the weather derivative. The present value of revenues R of a farmer who produces output Q and holds a position of the weather derivative is defined by:

$$(4)\quad R = \left(Q(I) * P + W(I)\right) * \exp(-r * T) - F,$$

where P is the product price, which is assumed to be constant for the sake of simplicity. Without insurance, the terms W and F vanish. Output Q is a function of the stochastic weather index I and other controllable or stochastic factors. Obviously, the risk-reducing potential of any weather insurance depends on the correlation between the weather index and the considered agricultural product. Further on, this relationship will be captured by the estimation of a "production function."

Analyzing the hedging effectiveness of risk management tools is usually carried out in an expected utility framework. A widely used utility function, which we also apply here, is the negative exponential:

$$(5)\quad U(R) = -\exp(-\lambda_a * R),$$

where λ_a is the absolute risk-aversion parameter. The effect of weather insurance can then be expressed in terms of certainty equivalence (CE):

$$(6)\quad CE = E^{-1}\left(U(R)\right).$$

Statistical Modeling of Weather Indexes

The previous section made clear that the probability distribution of the weather index I at the time of expiration is crucial to the assessment of any weather derivative. The distribution of the weather index influences the revenue distribution through the production function and the derivative payoff and also determines the cost of insurance, i.e., the derivative price.

From a statistical viewpoint, there are three alternatives with regard to the modeling of weather risk. On the one hand, the weather index distribution (e.g., cumulative rainfall in May) can be estimated directly, either parametrically or nonparametrically. On the other hand, the relevant weather index can be derived from a daily model of a generic weather variable (e.g., daily rainfall) through appropriate aggregation.

The corresponding approaches are the burn analysis (also referred to as burn rate method), the index value simulation, and the daily simulation. These modeling approaches are briefly described in turn. For a more thorough discussion, interested readers are referred to Jewson and Brix (2005, chapters 3, 4, and 6).

Burn Analysis

In a nonparametric burn analysis, the general pricing formula (1) is implemented in a simple manner:

$$(7)\quad F = \exp(-r * T) * \left[\frac{1}{n} * \sum_{t=1}^{n} W(I_t)\right].$$

Calculating (7) involves the following steps. First, weather data over a time horizon of n years are collected (and cleansed, if necessary). Next, the index value and the hypothetical payoffs of the derivative are determined for each year in the sample period. Finally, the payoff average is calculated and discounted with the risk-free interest rate r. This means that the burn analysis utilizes the empirical distribution of the rainfall index. No further statistical model is required.

Although this method is widely practiced, it has been criticized in the literature. Turvey (2005) states that a burn analysis is only backward-looking, and implicitly assumes that historical patterns will repeat themselves, while Cao, Li, and Wei (2003) report that derivative prices produced by this method are rather sensitive to the number of observations. Moreover, Jewson and Brix (2005)

emphasize that the burn analysis has difficulties predicting the occurrence of extreme weather events.

Index Value Simulation

An index value simulation follows steps similar to the burn analysis, but the empirical distribution is replaced by a statistical model for the weather index or the derivative payoff. This can be a nonparametric distribution, for example a kernel density, or a parametric distribution. The choice of the functional form of the distribution is usually based on theoretical considerations (e.g., a nonnegative domain for rainfall amounts) and is supported by goodness-of-fit tests.

Parameters of the distribution can be estimated from historical data with standard methods such as the method of moments or maximum likelihood. With an appropriate distribution, at-hand values for the precipitation index are randomly drawn and the discounted payoff of the derivative is determined. The derivative price is again obtained by calculating the average discounted payoff.

If the correct distribution is known and the parameters can be estimated precisely, then the index value simulation will produce more accurate results than the burn analysis, because random errors can be eliminated by choosing a sufficiently high number of random draws. However, in contrast to the modeling of financial variables, there is little theoretical guidance for modeling the distributions of weather indexes, and hence the danger exists of misspecifying the model.

Daily Simulation

Instead of modeling the weather index or the payoff distribution directly, one can alternatively develop a statistical model for the stochastic process of the underlying weather variable (daily rainfall or average daily temperature). Such a model describes the dynamics of the weather variable over time and can be used for simulation. The weather index can be derived from the simulated sample path by summing up daily precipitation or daily average temperature, respectively, in the relevant accumulation period. The subsequent steps for calculating the derivative price are identical to the index value simulation.

This procedure is initially more complex, yet potentially favorable for several reasons. First, the ways in which daily models can be used are very flexible, because practically all yield-relevant events such as the sums of precipitation or temperature for different accumulation periods, dry spells, or extreme precipitation can be determined for any time period. In contrast, directly estimating the weather index distribution is usually only valid for a particular index. Second—and this seems even more important than the higher flexibility—the accuracy of daily-based models is higher due to a considerably larger number of observed values (Brix, Jewson, and Ziehmann, 2002). If observations from N years are available to estimate the parameters of a weather index distribution, then $365 \times N$ observations can be used to estimate the stochastic process parameters of the underlying daily weather variable. Finally, daily simulation permits incorporating weather forecasts into the pricing model.

Presumably for these reasons, pricing and analyzing the effectiveness of temperature-related derivatives mainly originate from daily temperature models. Despite the aforementioned differences between the stochastic processes of temperature and rainfall, it seems promising to apply the daily modeling approach in the context of rainfall-based insurance. We pursue this idea in the next section.

A Daily Precipitation Model

A precipitation model should be able to capture the following characteristics of daily rainfall. First, the probability of rainfall occurrence obeys a seasonal pattern.

Rainfall in Europe, for example, is more likely in winter than in summer. Second, the sequence of wet and dry days follows an autoregressive process. This means the probability of a rainy day is higher if the previous day was wet. Third, the amount of precipitation on a wet day varies with the season. Rainfall in Europe is more intensive in summer than in winter. Fourth, the volatility of the amount of rainfall also changes seasonally. In Europe, it is higher in summer than in winter.

In the following, a daily precipitation model is described which can depict these characteristics. According to Moreno (2002) and Cao, Li, and Wei (2004), the stochastic process of daily precipitation can be decomposed into two parts: (*a*) a stochastic process for the binary event "rainfall" and "dryness," and (*b*) a distribution for the amount of precipitation given a rainy day. In order to specify the first component of the model, we define the random variable X_t:

$$(8)\quad X_t = \begin{cases} 0 & \text{if day } t \text{ is dry,} \\ 1 & \text{if day } t \text{ is rainy.} \end{cases}$$

It is assumed that X_t follows a first-order Markov chain. The probability (p_t) that it will rain on day t can be calculated as:

$$(9)\quad p_t = p_{t-1} * q_t^{11} + (1 - p_{t-1}) * q_t^{01}, \quad t = 1, 2, \ldots, 365,$$

where q_t^{01} describes the transitional probability of rain on day t and dryness on the previous day $t-1$. Analogously, q_t^{11} represents the transition probability between two successive rainy days. Note that the transition probabilities q_t^{01} and q_t^{11} vary with time.

The second part of the model, i.e., the precipitation amount y_t on day t, is represented by a sequence of continuous random variables with independent distributions. In the literature, various distributions with a nonnegative domain are discussed, including, among others, the exponential distribution and the gamma distribution (Woolhiser and Roldan, 1982). The mixed exponential distribution has proven to be especially flexible (Wilks and Wilby, 1999). The density function is given by:

$$(10)\quad f(y_t \mid X_t = 1) = \frac{\alpha_t}{\beta_t} * \exp\left(\frac{-y_t}{\beta_t}\right) + \frac{1-\alpha_t}{\gamma_t} * \exp\left(\frac{-y_t}{\gamma_t}\right),$$

with $0 \le \alpha_t \le 1$ and $0 < \beta_t < \gamma_t$.

The mixed exponential is a weighted combination of two simple exponential distributions and inherits their properties. The advantage of this distribution is that it can better represent extreme events compared with a simple exponential (cf. Hansen and Mavromatis, 2001). The parameters of the mixed exponential distribution α_t, β_t, and γ_t are also time-varying, thereby taking into account the seasonality of precipitation.

In this form, however, the model is not estimable. In order to reduce the number of parameters to be estimated, each of the time-varying parameters is developed by a finite Fourier series:

$$(11)\quad \theta_{tj} = a_{j0} + \sum_{k=1}^{m_j} \left[a_{jk} * \sin\left(\frac{t * k}{\tau} + b_{jk}\right)\right],$$

where $\theta_{t1} = q_t^{01}$, $\theta_{t2} = q_t^{11}$, $\theta_{t3} = \alpha_t$, $\theta_{t4} = \beta_t$, $\theta_{t5} = \gamma_t$, and $\tau = 365/(2 * \pi)$; a_{jk} and b_{jk} denote the Fourier coefficients; and m_j is the maximum number of harmonics needed to specify the seasonal cycles. The variable m_j can be determined by means of a model selection criterion, e.g., the Akaike information criterion (AIC). The Fourier coefficients for q_t^{01} and q_t^{11} are estimated by maximizing the following log-likelihood functions (Woolhiser and Pegram, 1979):

$$(12)\quad \ln L_1 = \sum_{t=1}^{365} \left[c_t^{00} * \ln(1 - q_t^{01}) + c_t^{01} * \ln(q_t^{01}) + c_t^{10} * \ln(1 - q_t^{11}) + c_t^{11} * \ln(q_t^{11})\right],$$

where c_t^{ij} denotes the observed number of transitions from state i at day $t-1$ to state j at day t.

In order to estimate the Fourier coefficients for α_t, β_t, and γ_t, we maximize the following log-likelihood function (Woolhiser and Pegram, 1979):

$$(13) \quad \ln L_2 = \sum_{t=1}^{n} \ln\left[f(y_t \mid X_t = 1)\right],$$

where n denotes the number of rainy days in the sample.

Based on this model, Wilks (1999) provides a computational procedure for the simulation of sample paths of daily rainfall. First, three independent uniform random variables, $u_{1,t}$, $u_{2,t}$, and $u_{3,t}$, are generated, with $u_{1,t}, u_{2,t}, u_{3,t} \in [0, 1]$. The sequences of wet and dry days (8) can then be simulated by comparing the estimated probabilities of daily rainfall occurrence (9) and $u_{1,t}$ as follows:

$$(14) \quad X_t = \begin{cases} 0 & \text{if } u_{1,t} > p_t, \\ 1 & \text{otherwise.} \end{cases}$$

For a rainy day ($X_t = 1$), the rainfall amount y_t^{sim} can be simulated according to:

$$(15) \quad y_t^{sim} = \tilde{y} - \varpi_t * \ln(u_{2,t}),$$

where $\tilde{y}$ is the minimal rainfall amount for a day to be recorded as rainy ($\tilde{y}$ equals 0.1 mm for weather stations in Germany). The parameter ϖ is chosen as:

$$(16) \quad \varpi_t = \begin{cases} \beta_t & \text{if } u_{3,t} \le \alpha_t, \\ \gamma_t & \text{otherwise.} \end{cases}$$

The sequence y_t^{sim}, $t = 1, 2, \ldots, 365$, facilitates determining one iteration of the considered rainfall index. The entire procedure is repeated 50,000 times.

Application: Valuation of Rainfall Options for Grain Producers in Northeast Germany

Grain production in northeast Germany, Brandenburg in particular, is highly affected by rainfall risk. During the relevant period of April to June over the last 20 years, average yearly rainfall in Brandenburg was between 64 mm and 258 mm of precipitation (with a mean of 151 mm), and the grain yields have fluctuated similarly. The correlation between rainfall and yields results from the sandy soil possessing little water-storing capacity, as well as the lack of irrigation. Currently there is no possibility of insuring against yield losses caused by low rainfall.

In view of the extreme crop failures in the drought years 2000 and 2003, during which time the government had to provide disaster relief in order to save farmers from insolvency, there is a pronounced interest in introducing some kind of rainfall insurance. By purchasing a put option on some rainfall index, a grain producer is (partially) insured against revenue losses due to little precipitation in the growing season. Prior to the analysis of the hedging effectiveness of a particular instrument, we investigated the properties of the historical simulation, the index value simulation, and the daily simulation for a variety of rainfall indexes.

Definition of the Rainfall Indexes

Two different types of precipitation indexes are defined: a cumulative rainfall index and a deficit index. The cumulative index (I^c) is the sum of daily rainfall amount in a certain accumulation period:

$$(17) \quad I^c = \sum_{t=1}^{x} y_t,$$

where x denotes the length of the accumulation period. We call this index the "rainfall sum." Existing empirical studies on rainfall insurance usually apply this type of index. As an alternative, we suggest a rainfall deficit index (I^d) defined as:

$$(18) \quad I^d = \sum_{\tau=1}^{z} \min\left(0, \sum_{t=(\tau-1)*s+1}^{\tau*s} y_t - y^{min}\right).$$

This index measures the shortfall of the rainfall sum in an s-days period relative

Table 1. Probability Distribution Functions Selected by Different Goodness-of-Fit Tests

	Rainfall Sum Index				Rainfall Deficit Index			
	— Accumulation Period —				— Accumulation Period —			
Goodness-of-Fit Test	**Jan–Dec**	**Mar–July**	**Apr–June**	**June**	**Jan–Dec**	**Mar–July**	**Apr–June**	**June**
Chi Square:	**Beta**	**Weibull**	**Beta**	**Pearson VI**	**Beta**	**Weibull**	**Beta**	**Beta**
▸ Test Value	3.90	4.41	7.30	11.96	6.50	6.84	10.28	9.00
▸ Critical Value*				16.92				
Kolmogorov-Smirnov:	**Weibull**	**Weibull**	**Gamma**	**Lognormal**	**Beta**	**Weibull**	**Beta**	**Beta**
▸ Test Value	0.08	0.07	0.07	0.08	0.05	0.06	0.12	0.07
▸ Critical Value*	0.87	0.87	1.36	1.36	1.36	0.87	1.36	1.36
Anderson-Darling:	**Weibull**	**Erland**	**Gamma**	**Lognormal**	**Beta**	**Weibull**	**Beta**	**Beta**
▸ Test Value	0.42	0.23	0.44	0.54	0.53	0.29	0.66	0.82
▸ Critical Value*	0.76	2.49	2.49	2.49	2.49	0.76	2.49	2.49

* Critical values at a 95% significance level.

to a reference level y^{min}. This shortfall is cumulated over z periods. Hence, the construction principle is quite similar to that of degree-day indexes, which are widely used for the specification of temperature derivatives.[1] The rainfall sum and the rainfall deficit are calculated for four accumulation periods: January 1–December 31, March 1–July 31, April 1–June 30, and June 1–June 30. The variable s is set to five days, and y^{min} equals the average five-day precipitation in the respective accumulation period.

Specification and Estimation of the Precipitation Models

Estimation of the rainfall index distributions is based on rainfall data measured in Berlin-Tempelhof from January 1, 1948 to December 31, 2005. This means $N = 58$ observations are available for estimating the empirical and the parametric distribution of the two rainfall indexes, and $n = 21{,}170$ observations for estimating the daily precipitation model. The most appropriate parametric distributions for the eight indexes are determined by means of three goodness-of-fit tests: the Chi-Square test, the Kolmogorov-Smirnov test, and the Anderson-Darling test.[2] That distribution which showed the smallest value of the respective test criterion was selected. Only distributions with a nonnegative domain for the rainfall sum and a nonpositive domain for the rainfall deficit were considered.

Table 1 displays the estimation results. For rainfall deficit, the beta distribution, in most cases, offers the best approximation to the empirical distribution. An exception is the accumulation period from March–July, where the Weibull distribution is more appropriate. The choice of a parametric distribution for the rainfall sum is more complicated, initially because more functions come into play, and additionally because the three statistical tests suggest different distributions for the same accumulation period. Considering this sensitivity, we did not select a single distribution for the index value simulation but ran two variants labeled "index value simulation I" (IVS I) and "index value simulation II" (IVS II) thereafter.

[1] This definition may appear unusual since the deficit index will take negative values. However, the definition is convenient for the present application because the relationship between the index and the production output is the same as for the rainfall sum.

[2] The calculations were carried out with BestFit. Detailed information on the properties and the assumptions of these goodness-of-fit tests can be found, for example, in D'Agostino and Stephens (1986) and Vose (2005, p. 240).

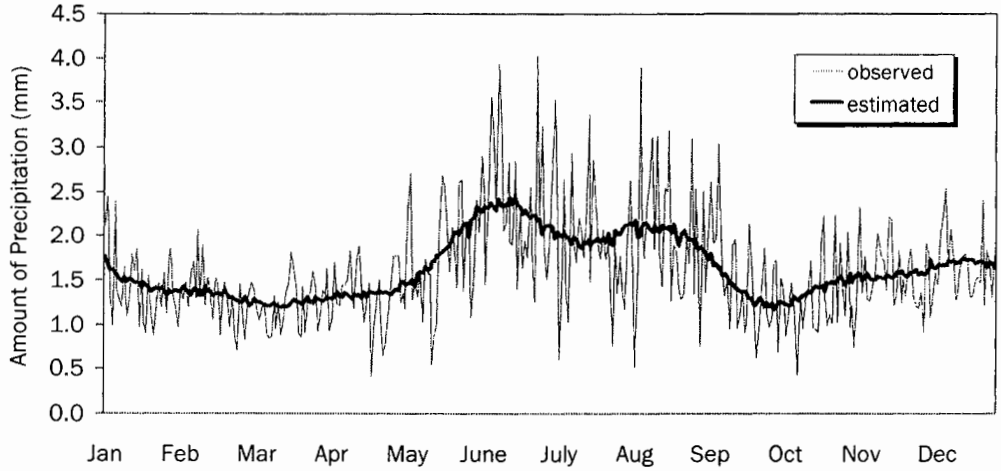


Figure 1. Observed and Estimated Average Daily Precipitation (weather station Berlin-Tempelhof)

To estimate the daily precipitation model parameters (8) to (11), the likelihood functions (12) and (13) were maximized with a genetic algorithm.[3] The assumption of a mixed exponential distribution for the daily rainfall amount is supported by a Kolmogorov-Smirnov test at a 95% significance level. The number of harmonics of the Fourier series, m_j, are determined using the Akaike information criterion (AIC). The AIC value is minimal for $m = 9$ in the case of the transition probabilities, and $m = 7$ in the case of the mixed exponential distribution parameters. Figure 1 shows the actual and the estimated daily rainfall over the course of a year. Figure A1 in the appendix depicts the corresponding transition probabilities q_t^{01} and q_t^{11}. Obviously, the model not only fits the yearly average, but also the seasonality of the rainfall amounts as well. From appendix Figure A2 it can be seen that the standard deviation of the estimated daily precipitation is actually higher in summer than in winter. Hence, the model reflects the aforementioned characteristics of daily rainfall.

[3] Genetic algorithms are heuristic search procedures which are able to solve complex optimization problems by mimicking the optimization strategy of biological evolution. For a detailed exposition, see Goldberg (1989) or Mitchell (1996).

A pitfall of the daily precipitation model is the underestimation of the cumulated rainfall variance over a period of several weeks. This underestimation of the variance has already been observed in a different context and has been termed "low frequency variability bias" (Hansen and Mavromatis, 2001; Dubrovsky, Buchtele, and Zalud, 2004). For example, the sample standard deviation of the cumulative precipitation from January–December is 95.09 mm, whereas the daily precipitation model only shows a value of 75.53 mm. One can expect that the daily simulation will also result in biased options prices because options prices are sensitive to volatility.

Hansen and Mavromatis (2001) discuss various methods for reducing the low frequency variability bias. In this study we take several measures. First, the transition probabilities q_t^{01} and q_t^{11} are estimated by their empirical sample counterparts, which clearly show a higher variability than those based on the Fourier series (see appendix Figure A1). Moreover, the parameters of the mixed exponential distribution α_t, β_t, and γ_t are determined in such a way that the resulting standard deviation exactly fit the sample standard deviation of the daily rainfall amounts shown in appendix Figure A2(b). Second,

Table 2. Comparison of Different Precipitation Models

PANEL A. Moments of the Rainfall Index

	Rainfall Sum Index				Rainfall Deficit Index			
	— Accumulation Period —				— Accumulation Period —			
Precipitation Model	**Jan–Dec**	**Mar–July**	**Apr–June**	**June**	**Jan–Dec**	**Mar–July**	**Apr–June**	**June**
BA:								
▸ Mean	578.32	257.13	160.34	69.54	-257.99	-116.31	-75.88	-29.52
	(11.94)	(7.31)	(6.43)	(5.23)	(4.82)	(2.35)	(2.26)	(1.59)
▸ Standard Deviation	95.09	53.46	51.37	40.21	37.48	18.79	17.13	13.04
	(7.92)	(4.84)	(3.54)	(5.72)	(2.60)	(1.59)	(1.68)	(1.04)
IVS I:	**Beta**	**Weibull**	**Beta**	**Pearson VI**	**Beta**	**Weibull**	**Beta**	**Beta**
▸ Mean	578.32	254.27	160.34	75.54	-257.99	-116.31	-75.88	-29.52
	(12.48)	(8.29)	(6.66)	(7.43)	(5.26)	(2.54)	(2.28)	(1.88)
▸ Standard Deviation	95.09	60.79	51.37	64.00	37.48	18.86	17.13	13.04
	(6.30)	(5.70)	(3.37)	(16.36)	(2.32)	(1.74)	(1.37)	(1.04)
IVS II:	**Weibull**	**Erland**	**Gamma**	**Lognormal**	**Beta**	**Weibull**	**Beta**	**Beta**
▸ Mean	572.86	256.69	160.34	70.57	[see IVS I]			
	(13.70)	(7.72)	(6.34)	(5.74)				
▸ Standard Deviation	105.73	53.44	51.99	45.66				
	(10.57)	(5.58)	(5.93)	(9.95)				
DS I:								
▸ Mean	578.72	257.10	161.54	68.13	-236.62	-108.27	-70.45	-28.16
	(9.76)	(5.71)	(5.25)	(5.07)	(3.79)	(2.51)	(1.69)	(2.05)
▸ Standard Deviation	75.53	51.93	42.91	29.24	28.41	19.62	15.91	11.46
	(5.87)	(4.74)	(4.92)	(3.68)	(2.37)	(1.75)	(2.06)	(1.22)
DS II:								
▸ Mean	579.21	256.31	160.91	69.15	-246.66	-113.89	-74.36	-30.09
	(8.95)	(6.96)	(5.95)	(4.24)	(3.12)	(2.67)	(1.99)	(1.76)
▸ Standard Deviation	83.26	56.35	46.03	32.15	29.65	20.55	16.74	11.82
	(6.94)	(5.00)	(4.90)	(4.13)	(2.42)	(1.89)	(1.69)	(1.11)

Notes: BA = burn analysis, IVS = index value simulation, DS = daily simulation; mean and standard deviation values are in mm; values for the put and call options are in €; values in parentheses are standard errors.

following Dubrovsky, Buchtele, and Zalud (2004), a second-order Markov process (as opposed to a first-order) is estimated. Thus, longer sequences of consecutive rainy and dry days, respectively, may occur, which leads to a higher standard deviation of the cumulated precipitation. In what follows, the original and the modified daily precipitation model are called "daily simulation I" (DS I) and "daily simulation II" (DS II), respectively.[4]

Results of the Precipitation Models

Panel A of Table 2 presents the mean and the standard deviation of the rainfall index distributions obtained by applying the burn analysis, the index value simulation, and the daily simulation.[5] The results of the parametric methods (index value simulation and daily simulation) are based on 50,000 repetitions. Consequently, sampling errors are virtually eliminated.

[4] In addition to these two models, other model versions have been specified and estimated. For example, the mixed exponential distribution has been replaced by a kernel density estimator as suggested by Rajagopalan, Lall, and Tarboton (1996). The results, however, did not change significantly.

[5] Note that the mean and the variance do not completely describe the index distributions presented in Table 2. Higher-order moments (e.g., skewness and kurtosis) may also differ. We focus here on the first two moments, since they are the most important determinants of the options prices considered below.

Table 2. Extended

PANEL B. Options Prices

	Rainfall Sum Index				Rainfall Deficit Index			
	— Accumulation Period —				— Accumulation Period —			
Precipitation Model	**Jan–Dec**	**Mar–July**	**Apr–June**	**June**	**Jan–Dec**	**Mar–July**	**Apr–June**	**June**
BA:								
▸ Put	37.04	20.56	20.15	13.82	14.95	7.10	6.31	5.16
	(6.94)	(3.95)	(3.59)	(2.26)	(2.77)	(1.30)	(1.47)	(0.95)
▸ Call	37.04	20.56	20.15	13.82	14.95	7.10	6.31	5.16
	(7.12)	(4.54)	(3.87)	(4.13)	(2.79)	(1.45)	(1.09)	(0.87)
IVS I:	**Beta**	**Weibull**	**Beta**	**Pearson VI**	**Beta**	**Weibull**	**Beta**	**Beta**
▸ Put	40.07	24.90	21.57	15.28	15.51	7.37	6.71	5.24
	(6.94)	(5.14)	(3.78)	(2.17)	(3.09)	(1.44)	(1.37)	(1.00)
▸ Call	37.93	22.14	20.81	21.06	15.89	7.37	7.03	5.18
	(7.19)	(4.51)	(3.71)	(6.49)	(2.70)	(1.56)	(1.25)	(1.14)
IVS II:	**Weibull**	**Erland**	**Gamma**	**Lognormal**	**Beta**	**Weibull**	**Beta**	**Beta**
▸ Put	43.05	20.75	19.78	15.09	[see IVS I]			
	(9.05)	(4.01)	(3.43)	(2.14)				
▸ Call	38.08	20.33	20.42	16.09				
	(7.25)	(4.89)	(4.20)	(4.61)				
DS I:								
▸ Put	28.67	20.02	15.32	11.93	3.38	4.33	3.90	3.85
	(4.40)	(3.24)	(2.98)	(2.09)	(0.82)	(1.15)	(1.20)	(1.16)
▸ Call	29.06	19.99	16.47	10.57	25.03	12.08	9.13	5.16
	(6.29)	(3.77)	(2.99)	(3.39)	(3.33)	(1.79)	(1.10)	(1.07)
DS II:								
▸ Put	31.33	21.95	17.37	12.42	6.78	6.83	5.76	4.89
	(4.85)	(3.72)	(3.50)	(2.25)	(1.35)	(1.47)	(1.28)	(1.09)
▸ Call	32.19	21.16	17.92	12.04	17.70	9.16	7.22	4.34
	(5.65)	(4.34)	(3.29)	(2.68)	(2.36)	(1.67)	(1.15)	(0.95)

In order to assess the reliability of the five models, panel A also displays the estimates' standard errors, which are calculated for 200 iterations using the bootstrap method.

In addition, the prices of a put and a call option on each of the eight rainfall indexes are calculated in Table 2, panel B to illustrate the consequences of statistical modeling for the valuation of weather derivatives. The options prices are calculated according to equation (1) using actual probabilities. The contract payoff W is $\max(S - I, 0) * V$ for the put option and $\max(I - S, 0) * V$ for the call option. The strike price S equals the sample mean of the respective indexes, and the tick size V is set to 1 € per index point. A risk-free discount rate of 5% and a maturity of nine months are assumed.

Using the empirical distribution generated by the burn analysis (BA) as a benchmark, we find from Table 2, panel A that the fit of the index value simulation and the daily simulation varies depending on the rainfall index. For example, the mean and standard deviation of the rainfall deficit from April–June and the month of June are estimated fairly well by all methods. In contrast, high deviations occur, for example, in the sum of rainfall in June.

The relative performance of the index value simulation and the daily simulation is also ambiguous. The index value simulation is superior to both variants of the daily

simulation for all variants of the deficit index in the sense that its estimates are closer to the mean and the standard deviation of the empirical distribution (which themselves are random variables). In contrast, the DS II outperforms the Pearson VI distribution in the case of the rainfall sum in June, and the Weibull distribution for the accumulation period March–July. As noted above, the DS I has particular problems in estimating the volatility of the rainfall index correctly. In almost all cases, the estimator is biased downward. This problem can be mitigated by modifications of the standard model described above, but in some cases the DS II still underestimates rainfall variability, while the index value simulation tends to overestimate the volatility. This bias can be considerable—e.g., for the rainfall sum in June.

The mean and standard deviation of the index distribution are important determinants of the corresponding options prices, and hence biased estimates of these parameters translate into incorrect derivative prices. The differences between the various estimation methods are pronounced for the annual period of rainfall deficit. Fair prices for the put option calculated with the daily simulation models amount to 3.38 € and 6.78 €, respectively, while the burn analysis and the index value simulation give an option price of about 15 €. It may also happen that estimation errors in the mean and in the volatility compensate each other, i.e., the resulting option price is right for the wrong reasons. This occurs, for example, when IVS I is used to price a put option on the rainfall sum in June.

An argument sometimes presented in favor of daily simulation is that this method produces small standard errors. Actually, the daily simulation shows smaller standard errors than the burn analysis and the index value simulation in many cases of the present application, but the gain in accuracy is not as pronounced as reported by Brix, Jewson, and Ziehmann (2002) for a temperature index. It may even be that the daily simulation has slightly larger standard errors than one of the other estimation procedures. Interestingly, the estimates of the burn analysis frequently have smaller standard errors than those of the index value simulation. Contrary to this observation, the burn analysis has been criticized in the literature for producing unstable results (see, e.g., Cao and Wei, 2003; Zeng, 2000).

Estimating the Relation Between Wheat Yield and Rainfall

Estimation of the yield model is based on the yield data of a single representative farm in Brandenburg over 13 years, from 1993 to 2005. Thirteen observations seem to be a poor database for the estimation of the yield model. However, a longer time series is not available for the new federal states in Germany in general and Brandenburg in particular, since production took place under totally different conditions prior to German reunification. Hence, yield data before and after 1990 cannot be pooled.[6]

Several functional forms for the yield model have been tested—in particular, a quadratic, a logarithmic, and a linear-limitational (Leontief) production function. The latter provided the best fit in terms of R^2 for the observed data and both indexes.[7] Another advantage of the Leontief production function is that it duplicates the payoff structure of a (plain vanilla) option. Specifically, if the yield can be modeled by a linear limitation function of the weather index, then an option on this index can be constructed which exactly offsets the revenues from production (if basis risk is nonexistent).

[6] This problem does not exist for regions in West Germany, but it is not possible to link a yield model that is calibrated for a region in West Germany with a rainfall model for Brandenburg.

[7] This finding cannot be generalized. Zhang (2003), for example, finds a quadratic production function more suitable for describing the relationship between wheat and rainfall. Vedenov and Barnett (2004) conclude that the appropriate weather-yield model varies by crop and region.

A linear-limitational production function is given by:

$$(19) \quad Q_t(I_t) = \begin{cases} d_0 + d_1 * I_t + \varepsilon_t & \text{if } I_t < d_2, \\ d_3 + \varepsilon_t & \text{otherwise,} \end{cases}$$

with $t = 1, 2, \ldots, 13$.

Here, d_0, d_1, d_2, and d_3 are parameters, and ε_t is the error term of the production function. The variable I_t represents, on one hand, the rainfall sum in June, and on the other hand the rainfall deficit in the period from April 1–June 30 (with $s = 5$ and $y^{min} = 6.4$ mm).

Table 3 presents the estimated parameters of the production function. The associated test statistics show that the fit of the production function is much better for the rainfall deficit than for the rainfall sum. The magnitude of the production function estimation errors will affect the hedging effectiveness of the rainfall insurance, and therefore it is important to understand their occurrence. The rather low fit of the yield models can be partly attributed to the shortness of the yield time series. Moreover, the residuals of the regression include both production risk and geographical basis risk, since the considered farm site is located at a distance of about 40 kilometers from the weather station.

Analysis of the Hedging Effectiveness of Two Rainfall Options

At this point, we have specified all model components necessary to investigate the hedging effectiveness as described earlier. We consider two put options: the first option refers to the rainfall sum in June, while the rainfall deficit in the period from April 1–June 30 underlies the second option. These particular specifications were chosen because the correlations between the indexes and the wheat yield are then maximized. The strike levels for the two options are 130 mm and 33.7 mm, and the corresponding values for the tick size amount to 1.9 €/index point and 8.1 €/index point. Again, these parameters are determined in such a way that the hedging effectiveness of the two derivatives is maximized.

The stochastic values of the rainfall indexes are generated by means of the index value simulation (lognormal distribution for the rainfall sum and Beta distribution for the rainfall deficit) and the modified daily simulation by using 50,000 repetitions. The basis risk that is inherent to the two options is captured by the normally distributed stochastic component of the estimated production functions. When simulating the stochastic revenues according to equation (4), a constant product price of 10 €/dt is assumed.

Table 4 presents selected parameters of the revenue distribution functions with and without rain insurance, as well as their certainty equivalents. The latter refer to the negative exponential utility function with an absolute risk-aversion parameter $\lambda_a = 0.01$.[8] Note that the expected value of the profit distributions does not change when buying the option, because the option price is calculated as the expected value of the payoffs with respect to the actual probabilities.

As explained earlier, this procedure implies a weather risk market price of zero and can be justified if the rainfall index and the market portfolio are uncorrelated. In the case of a positive correlation, the expected value of the weather index at expiration should be corrected downward, thus yielding a higher price for the put options, i.e., the cost of insurance would be higher. Moreover, sellers (insurance companies, banks) will presumably charge additional premiums to cover their transaction costs. Hence, actual prices are expected to be higher than the prices reported in Table 4. This leads to a downward shift of the revenue distributions with insurance.

[8]This choice of λ_a implies rather strong risk aversion (cf. Benitez et al., 2006).

Table 3. Estimation of Production Functions and Associated Test Statistics

Parameters	Estimation	*t*-Value	Critical Value of *t* (95%)	R^2	*F*-Value	Critical Value of *F* (95%)
Rainfall Sum Index:						
d_0	52.0	7.22				
d_1	0.19	1.83		0.22	2.82	
d_2	130.0	—				
d_3	77.0	3.48	1.81			4.96
Rainfall Deficit Index:						
d_0	103.0	13.01				
d_1	0.81	4.97		0.52	10.73	
d_2	-33.7	—				
d_3	75.5	2.34				

Table 4. Hedging Effectiveness

Precipitation Model	Put Option	Option Price	Parameters of the Revenue Distribution: Mean	Standard Deviation	5%	95%	Certainty Equivalent
Rainfall Sum Index:							
IVS	Without		624.13	117.89	434.39	821.79	548.06
	With	117.21	624.13	99.79	459.96	788.24	561.59
DS II	Without		626.62	114.06	437.94	815.66	552.56
	With	113.29	626.62	100.11	461.24	792.07	564.03
Rainfall Deficit Index:							
IVS	Without		619.76	119.36	411.00	803.47	523.83
	With	107.11	619.76	78.18	491.15	748.30	574.42
DS II	Without		624.02	115.82	424.61	805.73	546.55
	With	103.73	624.02	78.37	494.93	753.13	576.25

Notes: IVS = index value simulation, DS = daily simulation; all values are in €.

In contrast to other applications (e.g., Stoppa and Hess, 2003), risk reduction using a put option on the rainfall sum is limited here due to high basis risk. The volatility of revenues with insurance is only about 15% smaller than without insurance, and the certainty equivalent increases by 2%. This result is not surprising considering the small correlation between the rainfall sum and the wheat yield. The hedging effectiveness is higher for the rainfall deficit and amounts to one-third in terms of a reduction of the standard deviation; this finding emphasizes the importance of defining an appropriate weather index. As demonstrated below, the effect of rainfall insurance may be dampened or amplified the farther or closer a farm is located in relation to the weather station.

From a methodical viewpoint, it is interesting to compare the two valuation methods. Table 4 shows that the revenue distributions of the index value simulation and the (modified) daily simulation do not differ significantly. Additionally, both approaches calculate nearly the same hedging effectiveness. The largest difference amounts to a 4% variation for the certainty equivalent in the case of the deficit index. This is

remarkable since Table 2 showed considerable differences in the estimation of the mean and the standard deviation of the index distributions, in particular for the rainfall sum in June. The reason for this is that the index distributions of the rainfall sum generated by the index value simulation and the daily simulation differ mainly in the right tail, though these differences are aligned by the constant segment of the linear-limitational production function. However, this finding does not mean that the choice of modeling approach is unimportant. Other situations may exist where differences in the estimated rainfall distribution are translated more directly into the revenue distribution.

Analysis of Geographical Basis Risk

The existing empirical literature is equivocal with regard to the hedging effectiveness of weather derivatives in agriculture (see, e.g., Chen and Roberts, 2004; Edwards and Simmons, 2004; Fleege et al., 2004; Schmitz et al., 2004; Vedenov and Barnett, 2004; Manfredo and Richards, 2005). This is not surprising since the hedging effectiveness depends on several factors, which vary between applications. First, the correlation between the weather index and the yield is important. The correlation itself depends on the definition of the index and the considered product. Second, the quantification of the weather-yield relationship is subject to estimation errors, which can be pronounced. Third, the geographical basis risk has to be taken into account.

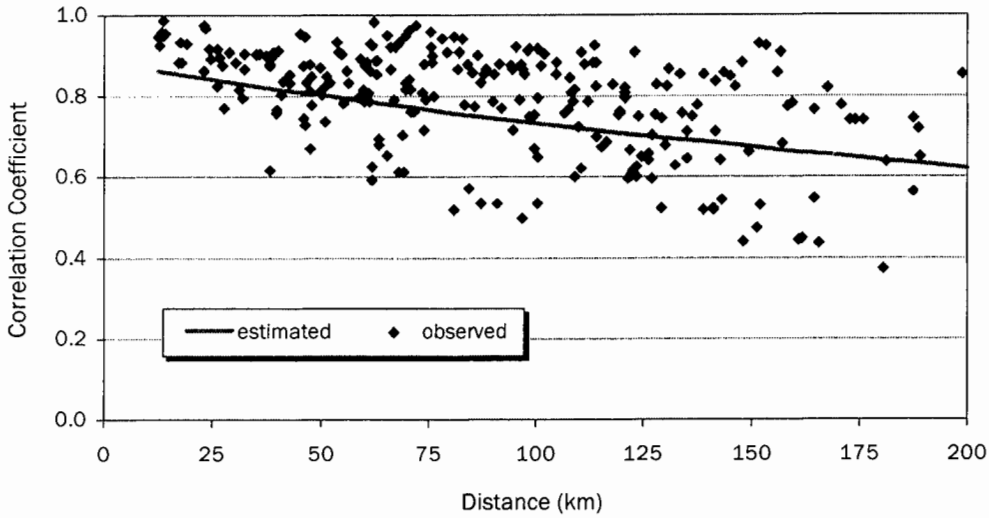
The first two issues have been discussed. Now we attempt to assess the magnitude of geographical basis risk that is inherent to the considered rainfall options by means of a de-correlation analysis. Rubel (1996) proposes the following nonlinear de-correlation function for the spatial relationship of precipitation in Europe:

$$(20) \quad \rho(d) = e_1 * \exp\left(-e_2 * d^{e_3}\right),$$

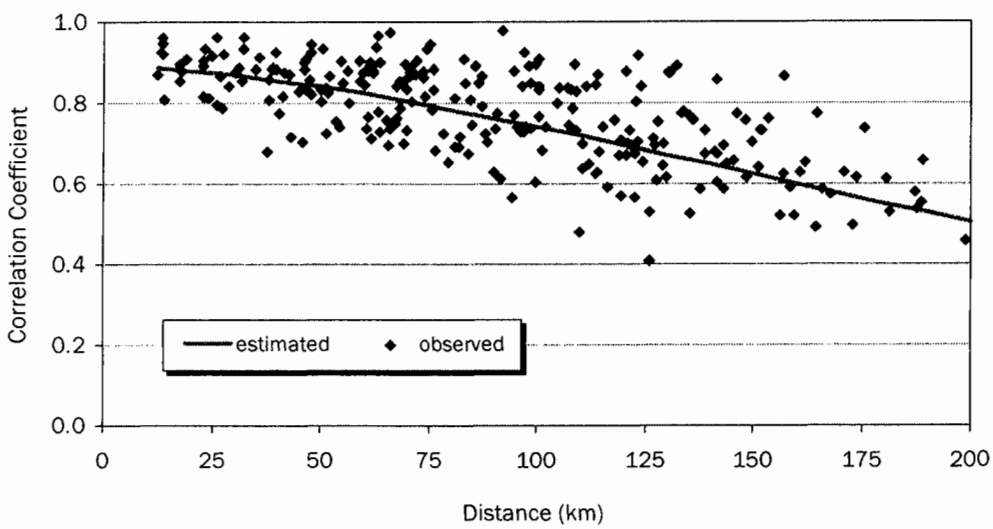
where $\rho(d)$ denotes the correlation coefficient between precipitation at different places, and d is the distance between the weather station and the farmer's production site. The variables e_1, e_2, and e_3 are parameters to be estimated. In spite of the de-correlation analysis being a popular instrument in meteorology, two points should be considered critically. First, the de-correlation function is invariant regarding direction. Thus, topographical differences potentially influencing precipitation are neglected. Second, Embrechts, McNeil, and Straumann (1999) identify problems of using correlation coefficients when the underlying distributions are not elliptical. Despite these weaknesses, de-correlation analysis is used in this study.

Calculation of geographical basis risk is carried out for both considered rainfall indexes (i.e., rainfall sum in June and rainfall deficit from April 1–June 30). Rainfall records for 23 weather stations in the Berlin and Brandenburg region are available between January 1983 and December 2003. For each weather station, a time series of the two rainfall indexes is calculated, and pairwise correlation coefficients are determined. Next, the distances between the stations are measured and entered into the nonlinear regression function (20). Parameter estimates for the de-correlation function are: $e_1 = 0.94$, $e_2 = 0.0033$, and $e_3 = 0.88$ for the rainfall sum, and $e_1 = 0.89$, $e_2 = 0.0001$, and $e_3 = 1.63$ for the rainfall deficit.

Figure 2 shows the graphs of the de-correlation functions which, as expected, have a negative slope. The R^2 for the rainfall sum is 0.24 and for the rainfall deficit 0.63. Therefore, the estimated de-correlation function is a better approximation to the empirical correlations in the case of the rainfall deficit. Moreover, the scatter plot reveals heteroskedasticity, i.e., the relationship between distance and correlation becomes less precise with increasing distance.



(a) Rainfall Sum



(b) Rainfall Deficit

Figure 2. De-correlation Function for Precipitation in Brandenburg, Germany

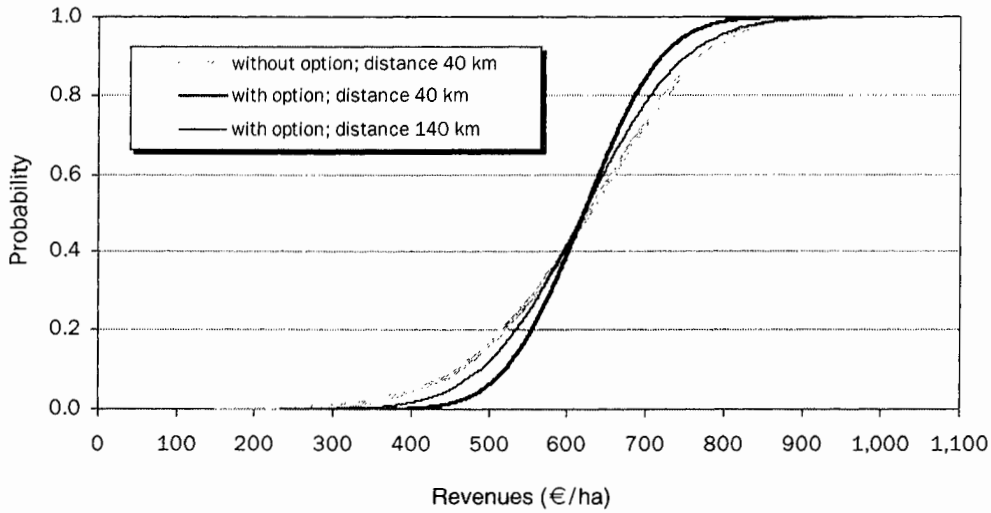


Figure 3. Revenue Distributions With and Without Hedging

From Figure 2 it can be seen that the correlation between Berlin-Tempelhof and a weather station 40 km away is approximately 0.87 for the rainfall sum and 0.86 for the rainfall deficit. These values decrease to about 0.65 and 0.5, respectively, at a distance of 200 km. This decrease is very moderate and related to the particular topographical situation in Brandenburg.[9]

Finally, we investigate the relationship between geographical basis risk and hedging effectiveness. This relationship is exemplified for the put option on the rainfall deficit index from April 1–June 30 using the index value simulation. The setting of the calculation is as before, but a second farm, which is located at a distance of 140 km from the reference weather station instead of 40 km, is also considered. According to the estimated de-correlation function, the correlation of the rainfall deficit index at these two farm locations is 0.74.

[9] Salson and Garcia-Bartual (2003) report a correlation of only 0.3 at a distance of 10 km in a Mediterranean region. Paulson and Hart (2006) estimate a correlation coefficient of approximately 0.6 for one degree of latitude (110 km) in Iowa, USA. East (2005) finds a de-correlation similar to ours for southeast Australia.

Figure 3 shows that the hedging effectiveness of a put option is considerably reduced the farther away from the reference weather station the producer is located. The standard deviation of the revenues is 78.18 at a distance of 40 km and 103.38 at a distance of 140 km. That is, more than half of the risk-reducing potential of the put option vanishes if the distance between the farm location and the reference weather station increases by 100 km.

Conclusions

In this paper we investigate three statistical approaches that can be used for modeling rain risk and pricing rain insurance. Our main interest lies with the question of whether a daily precipitation model can improve the estimation of rainfall indexes (and thereby the valuation of an index-based insurance) using simpler approaches such as burn analysis and index value simulation for comparison. Our results indicate that clear differences in the estimation results may occur among the three approaches. This finding underscores the importance of the model choice. However, it is difficult to draw an unequivocal conclusion regarding the superiority of a specific valuation approach.

Insofar as our results do not confirm others' previous experience in the context of temperature modeling, daily simulation is generally preferred. On the one hand, applying daily simulation has the advantage of yielding smaller confidence intervals for the resulting indexes and prices compared with the nonparametric burn analysis and the index value simulation, though this advantage seems to be much smaller for rainfall than for temperature. On the other hand, the danger of a rather sophisticated daily precipitation model being wrongly specified is relatively high; such a risk is precluded when the precipitation index is estimated directly.

In the present application, the daily simulation model tends to underestimate the volatility of monthly rainfall. This pitfall may be of minor importance in the context of meteorological or hydrological applications, but it is severe when the model is used for risk assessment and derivative pricing. Some measures to reduce this bias have been discussed and successfully implemented in this paper. Nevertheless, the problem deserves further attention.

Another shortcoming of the presented daily rainfall model is the ignorance of long-term (interannual) variability of the parameters. This means that trends, or an increase of rainfall volatility due to climatic changes, are not captured by this model. In principle, however, it is also possible to incorporate interannual variability into daily precipitation models (cf. Wilks and Wilby, 1999). We conclude that the preferential statistical approach to weather derivative pricing depends on the context of its application. Ideally, more than one model should be implemented, and differences of the models' outcomes should be carefully analyzed. A systematic model validation based on quasi-ex ante forecasts is suggested as a subject for further research.

Regardless of the issue of the appropriate statistical method, the following practical conclusions can be drawn. The risk-reducing effect of precipitation derivatives is much more regionally confined than is the case with temperature-related derivatives. In the example of Brandenburg considered here, the correlation between the precipitation index of the weather station Berlin-Tempelhof and a remote farm site decreases to a value of 0.75 at a distance of 100 km. If one additionally takes into account the stochastic relation between precipitation and production, the use of rainfall derivatives as risk management tools in agriculture appears questionable, at least for conditions comparable to those in this study.

It follows that potential suppliers of rainfall insurance should introduce a dense network of weather stations as reference points for the rainfall index in order to increase the attractiveness of this type of insurance, although this may lead to fragmented demand. Moreover, the specification of adequate weather indexes also requires further study. Simple rainfall indexes, upon which we focus here, may not be specific enough from the viewpoint of many producers. The inclusion of additional weather variables in the weather index (e.g., temperature or humidity) could help mitigate the problem of basis risk.

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Appendix

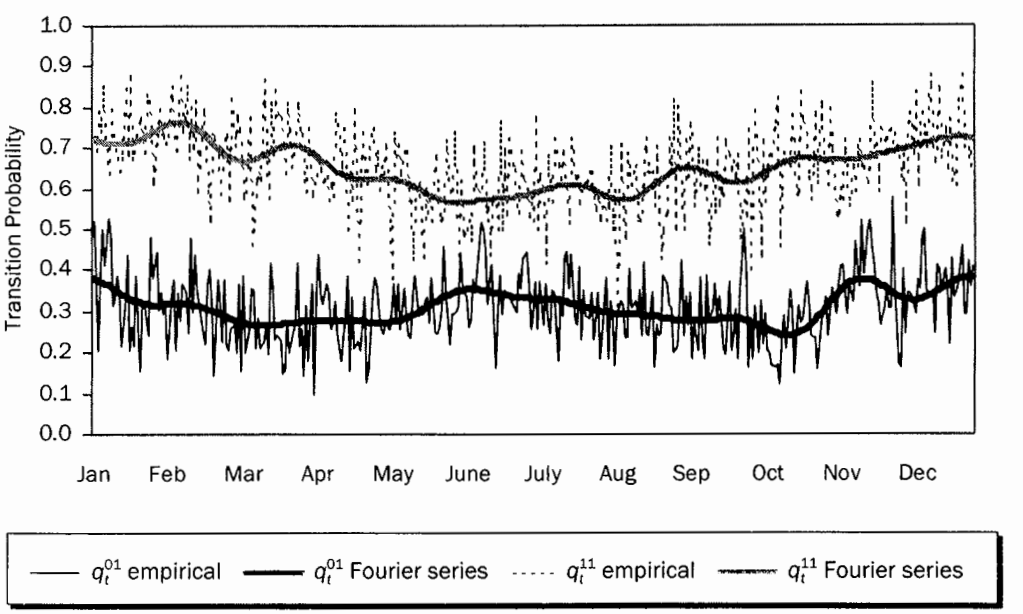
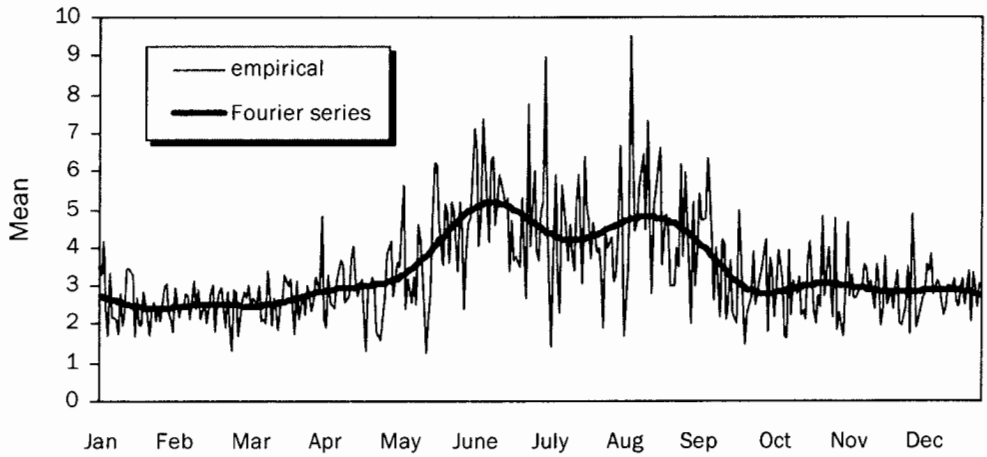
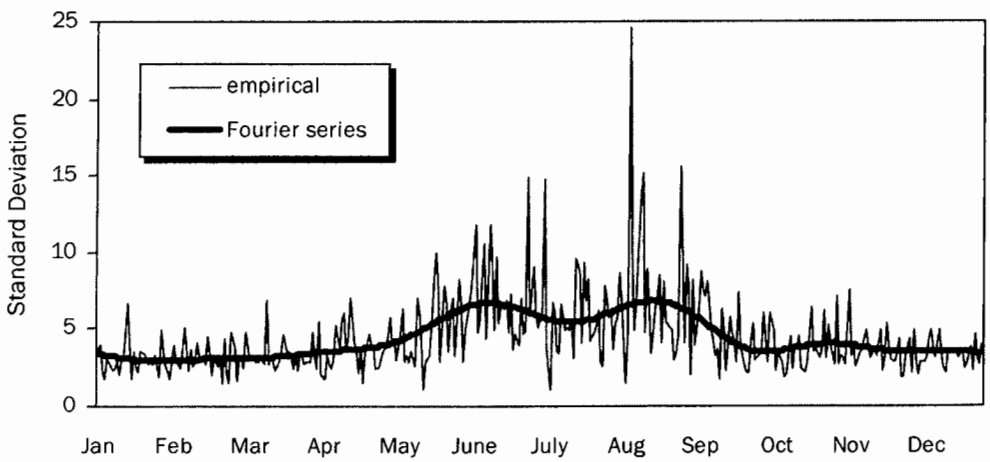


Figure A1. Conditional Transition Probabilities



(a) Mean



(b) Standard Deviation

Figure A2. Conditional Mean and Standard Deviation of Daily Precipitation

Evaluation of Risk Management Alternatives for Indiana Grain Producers

Ana R. Rios and George F. Patrick

Abstract

Crop insurance and pre-harvest pricing strategies were analyzed for "all years" and "years following a normal crop year" scenarios for the 1986 through 2001 period in three Indiana counties. Crop insurance products and early spring pre-harvest marketing generally had positive returns for producers. A large number of strategies provided higher mean revenues, higher 5% values-at-risk, and higher certainty equivalents than the benchmark strategy. Although pre-harvest marketing strategies had the highest certainty equivalents in both scenarios, net farm revenues were lower and crop insurance combined with pre-harvest pricing were common among top-ranked strategies following normal crop years.

Key words: crop insurance, pre-harvest pricing, risk management

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Agricultural producers face a changing set of prices, yields, and government policies. A variety of risk management strategies exist that may reduce the risks associated with farming. These risk management strategies are commonly grouped into production, marketing, and financial strategies. Production strategies reduce the variability of production. Marketing strategies reduce the variability of prices or transfer the price risk. In contrast, financial strategies generally increase the firm's capacity to bear risk (Patrick, 1998).

Risk management strategies may have different effects, but no single strategy can protect a producer from all types of risk. As a result, most producers use combinations of production, marketing, and financial strategies. Furthermore, the effectiveness of risk management strategies may be influenced by price and yield risks, risk-return tradeoffs, and risk preferences of an individual producer.

Over the past 50 years, a number of changes in the U.S. agricultural sector have increased the risks faced by producers and the importance of risk management. The fundamental shifts in the risk environment include the globalization of markets, increased managerial complexity, increased neighbor conflicts, and increased governmental regulations (Musser and Patrick, 2001). Additionally, the types of forward pricing contracts and crop insurance alternatives available have expanded, crop insurance premium subsidies have increased, and the loan deficiency and countercyclical payments of the Farm Security and Rural Investment Act (FSRIA) of 2002 may have

affected the risk management environment of producers.

The variety of risk-mitigating tools and changes in the agricultural sector have given rise to many studies seeking to understand how risk management strategies affect the level and variability of farm income. A number of analyses have determined the benefits, costs, and possible consequences associated with the implementation of a particular strategy or combination of strategies in different geographic locations and time periods (e.g., Dhuyvetter and Kastens, 1999; Nydene, 1999; Philpot, Larson, and Stokes, 2000; Clow and Flaskerud, 2001; Coble and Knight, 2001; Collins, 2001; Schnitkey, Sherrick, and Irwin, 2003; Pritchett et al., 2004, and Hagedorn et al., 2005). Some of these studies have reached conflicting conclusions, due in part to differences in the risk environments analyzed. Despite these efforts, it is not fully understood how risk management strategies affect the level and variability of net farm revenue for producers. In addition, there may be differences in the effectiveness of risk management strategies for different geographical areas and different market conditions.

In this study, the impact of expansion of crop insurance alternatives, increases in premium subsidies, and loan deficiency and countercyclical payments of the 2002 FSRIA are included in the evaluation of risk management strategies through a farm-level simulation model. The level and variability of net farm revenues are analyzed by several criteria and compared against a benchmark strategy of no insurance with cash sale at harvest as well as other management strategies.

This study builds on the work of Schnitkey, Sherrick, and Irwin (2003), who examined the effect of multi-peril crop insurance products on Illinois corn gross revenue distributions, and the work of Pritchett et al. (2004), who evaluated the impact of mechanical pre-harvest marketing alternatives and insurance products on Indiana corn and soybean gross revenue distributions. Using spreadsheet simulation methodology similar to Pritchett et al., we extend the analysis to consider different geographic areas and market conditions.

Specifically, this study evaluates the impact of risk management strategies on net farm revenue in three Indiana counties that differ in the level and variability of farm-level yields. The strategies are also analyzed under two different scenarios: "all years" and "years following a normal crop year." Typically, years following a short crop year—defined as a year in which production fell below the previous year's total utilization and the U.S. average yield was at least 5% below the long-run trend yield (Wisner, Blue, and Baldwin, 1998)—have high early spring prices. Because these conditions can be observed by producers and might lead to different marketing strategies, only years following a normal crop year are considered in the second scenario. Thus, this study seeks to understand how specific risk management strategies affect the level and variability of net farm revenue under different market conditions.

Theoretical Framework

The impact of risk management strategies on the level and variability of net farm revenue was evaluated following Schnitkey, Sherrick, and Irwin (2003), and Pritchett et al. (2004). This study draws heavily on the theoretical framework of Pritchett et al. and extends the analysis into additional geographical areas and market conditions.

The model did not explicitly consider production costs and direct government payments in the calculation of net farm revenue under the assumption that these costs and payments were constant across strategies. Therefore, net farm revenue was determined by gross revenue less the variable costs of risk management for each strategy. Revenue was based on farm-level yields and harvest prices, gains or losses from marketing strategies, and insurance

indemnity payments. Revenue also included any loan deficiency payments (LDPs) and countercyclical payments (CCPs) for corn and soybeans. The marketing contract commission fees, interest costs on futures and options margin accounts, and insurance administrative fees and premiums were considered as variable costs of risk management. Per acre revenues for an individual crop are expressed as:

$$(1) \quad R = r_c + r_{i,j} + r_m + r_g,$$

where r_c denotes the cash revenues for the crop harvest cash sales; $r_{i,j}$ represents indemnity payments received for the crop using the *i*th insurance product at the *j*th coverage level; r_m signifies the revenues from marketing strategies including hedging with futures, options, and forward contracting; and r_g represents the LDP and CCP payments received.

The no insurance, cash sale at harvest strategy was the benchmark for comparison of the risk management strategies evaluated. The farm's total production of soybeans was assumed to be sold on the cash market on October 1 and on November 1 for corn. Revenues from harvest cash sales equal the harvest futures price (f_1) minus the harvest local basis (b_1) times yield (y), or:

$$(2) \quad r_c = (f_1 - b_1)y.$$

Crop Insurance Indemnity Payments

The crop yield and crop revenue insurance products available in Indiana in 2002 were all incorporated in the analysis at different coverage levels and price elections. These included the individual farm-based Actual Production History (APH) and the county-based Group Risk Plan (GRP) yield insurance. Crop Revenue Coverage (CRC), Income Protection Plan (IP), Revenue Assurance (RA) with both the base and harvest price options, and Group Risk Income Plan (GRIP) were also included.

APH and GRP indemnities occur as a result of yield shortfalls only. The indemnity prices are determined prior to planting, and these insurances provide no price protection for producers. In contrast, for the other insurance products analyzed, indemnities are based on a combination of price and yield guarantees. In all cases, prices are based on the futures prices for specific periods, not the price received by an individual producer. Calculation of indemnity payments for the crop yield and crop revenue insurance products is detailed below.

- *Actual Production History* (*APH*). APH yield insurance makes payments when the actual yield is below the yield guarantee, and indemnities are calculated as:

$$(3.1) \quad r_{aph,j} = \left[p_{aph} * \max(0, y_{aph} * c_{aph,j} - y)\right] - x_{aph,j},$$

  where p_{aph} is the indemnity price determined by the Federal Crop Insurance Corporation (FCIC), c_{aph} is the coverage level, and $x_{aph,j}$ is the premium paid for the insurance at the *j*th coverage level.

- *Group Risk Plan* (*GRP*). GRP indemnities are paid when the actual county yield (y_c) falls below the expected county yield (y_{ec}) times the trigger level:

$$(3.2) \quad r_{grp,j} = \max\left(0, w_{grp} * (y_{ec} * c_{grp,j} - y_c)/(y_{ec} * c_{grp,j})\right) - x_{grp,j},$$

  where w_{grp} is the protection level, $c_{grp,j}$ is the coverage level, and $x_{grp,j}$ is the premium.

- *Crop Revenue Coverage* (*CRC*). An indemnity is paid when actual gross revenue falls below a revenue guarantee. The revenue guarantee uses the higher of a spring futures price (f_b) or a harvest price (f_h). Indemnity payments are calculated as:

(3.3) $r_{crc,j} = \max(0, \max(f_b, f_h) * y_{aph} * c_{crc,j} - f_h * y) - x_{crc,j}$.

- *Income Protection (IP).* IP indemnity payments are made when gross revenue falls below a guaranteed level. The guarantee level is calculated using a spring futures price, while the harvest price is used to calculate the actual gross revenue. IP's indemnity payments are expressed as:

(3.4) $r_{ip} = \max(0, (f_b * y_{aph} * c_{ip}) - f_h * y) - x_{ip,j}$.

- *Revenue Assurance (RA).* The revenue guarantee of RA is calculated by multiplying the APH yield by the coverage level and the price guarantee. Two price guarantees are available in RA: the Harvest-Price (RA-HP) option whose pricing rule is similar to CRC, and the Base-Price (RA-BP) option whose pricing rule is similar to IP. The RA-HP indemnity is calculated as:

(3.5) $r_{ra\text{-}hp} = \max(0, \max(f_b, f_h) * y_{aph} * c_{ra\text{-}hp,j} - f_h * y) - x_{ra\text{-}hp,j}$.

Indemnity payments for RA-BP use the spring futures price (f_b):

(3.6) $r_{ra\text{-}bp} = \max(0, f_b * y_{aph} * c_{ra\text{-}bp} - f_h * y) - x_{ra\text{-}bp,j}$.

- *Group Risk Income Plan (GRIP).* GRIP pays indemnities when county revenue is below a revenue guarantee. Indemnity payments are equal to:

(3.7) $r_{grip,j} = \max(0, w_{grip} * (f_b * y_{ec} * c_{grip,j} - f_h * y_c) / (f_b * y_{ec} * c_{grip,j})) - x_{grip,j}$.

Revenue from Marketing Strategies

Pre-harvest mechanical marketing strategies involving cash-forward contracts, hedging with futures contracts, and hedging with options contracts were evaluated in this study. These strategies were implemented at 33%, 66%, and 100% of the estimated 10-year moving average APH yield, the expected production assumed. Thus, the expected production was rounded to the nearest 5,000 bushel unit when trading futures or options.

- *Forward Contracts.* Revenues from forward contracts are calculated as follows:

(4.1) $r_m = p_c * y_c$,

where p_c is the forward contract price quoted in the spring and y_c is the size of the contract. In cases when the actual production is over-contracted ($y_c > y$) or under-contracted ($y_c < y$), it is assumed that a producer may need to buy replacement bushels to meet contract requirements or may sell the extra bushels at the harvest-time cash prices.

- *Futures Contacts.* December corn and November soybean futures contracts were used in the analysis. Proceeds from future hedges equal:

(4.2) $r_m = (f_0 - f_1) * h - x_h$,

where f_0 is the spring quoted price, f_1 is the harvest futures price, h is the hedged quantity, and x_h represents hedging costs of brokerage charges and interest on margin accounts.

- *Options Contracts.* Producers may also manage their price risk by using put options on futures options. Options hedges are exercised only if the futures price at harvest (f_h) is less than the strike price (f_s). Proceeds from options hedges are specified as:

(4.3) $r_m = \max(0, (f_s - f_h) * h) - x_{opt}$,

where x_{opt} includes brokerage charges and interest cost of the options hedge.

Government Payments

Government payments included LDP and CCP payments for corn and soybeans. For LDP payment calculations, the harvest-time cash price was assumed to be representative of posted county prices. LDP and CCP payments were based on county loan rates, direct payment rates, and target prices for the 2002–2003 time period.[1]

Simulation Procedures

Net farm revenue, cash market sales, crop insurance indemnities, marketing revenues/losses, and government payments were calculated for a model farm following the Pritchett et al. (2004) simulation procedures. The Pritchett et al. procedures are extended to remove trends and cycles from historical prices and yields. The model utilizes a historical bootstrapping procedure to simulate net farm revenue. A model iteration begins when a year within the historical period analyzed is drawn from a uniform distribution. The randomly drawn year determines the associated futures contract prices, county-level yields, insurance premium rates based on APH yields, and spring and harvest prices. As discussed later, farm-level yields for corn and soybeans are also generated. This information is then used to calculate the net farm revenue under each of the risk management strategies included in the study. Thus, with each random draw of a year, all of the variables previously mentioned are altered. The model was iterated 1,000 times with different farm-level yields, and the resulting 1,000 net farm revenue outcomes were used to create the net farm revenue distribution for each risk management strategy.

Given that prices and yields are historical data, the variability in the results generated by using raw data may be overestimated due to the trend of increasing yields and possible cyclical patterns of prices. To avoid this overestimation, an autoregressive moving-average (ARMA) process and detrending procedures are used to remove trends and cycles in the input data. An ARMA procedure in natural logarithms was used in the estimation of expected prices while taking into account interdependencies between successive observations.[2] This procedure takes the following form:

$$(5)\quad p_t = \delta + \varphi p_{t-1} + e_t - \theta e_{t-1},$$

where p_t is the natural logarithm of price in year t, with t including the 1986–2001 period in Carroll and Elkhart counties and the 1987–2001 period in Posey County; p_{t-1} is the natural logarithm of price in year $t-1$, e_t is the random noise in year t, and e_{t-1} is the random noise in year $t-1$.

Expected yields were calculated by a regression equation of trend in the yearly historical data. To eliminate the effects of inflation in prices and trends in yields over time, the time series were adjusted by an index using 2001 as the base period:

$$(6)\quad Detrended\ x_t = E(x)_{2001} \times (1 + \%e_t),$$

where x_t is the value of price or yield in year t, $E(x)_{2001}$ is the expected value of x in 2001, and $\%e_t$ is the percentage deviation from trend in year t. After removing the time trend, prices were converted back to the original measurement units by an exponential transformation. Therefore, although the specific conditions of the 2001 year are not simulated, the 1,000 iterations generated reflect prices measured in 2001 dollars and farm-level yields assuming 2001 technology levels.

[1] The county loan rates were $2.03 per bushel for corn and $5.12 per bushel for soybeans in Carroll County, $1.98 per bushel for corn and $5.03 per bushel for soybeans in Elkhart County, and $2.16 per bushel for corn and $5.21 per bushel for soybeans in Posey County. Target prices were $2.60 and $5.80 per bushel for corn and soybeans, respectively.

[2] The ARMA procedure was applied in the estimation of cash prices, average marketing year prices, futures prices, prices of puts and calls, strike prices, and insurance guarantee prices.

The analysis was conducted on a per acre basis for a 50/50 corn and soybean rotation. Three Indiana counties were chosen to represent areas with differing levels of yields, yield variability, yield/price correlation, and proximity to demand centers. Carroll County in central Indiana is a high-yield region with considerable yield variability, located in proximity to processing centers. Elkhart County in northern Indiana is an area with lower corn and soybean yields with lower yield variability, and limited local markets. Posey County, near the Ohio River in southwest Indiana, is an area of moderate corn and low soybean yields, with somewhat higher yield variability, and good access to international markets.[3]

Two crop year scenarios were analyzed. First, all years in the 1986–2001 period were considered. Second, the analysis was restricted to only those years following a normal crop year. Years following a short crop year, i.e., years when a weather-induced decline caused production to fall below the previous year's total utilization and the U.S. average yield was at least 5% below the long-run trend line yield (Wisner, Blue, and Baldwin, 1998), were excluded.[4] Producers can observe the occurrence of a short crop year and may adjust in response to the generally higher early spring prices following a short crop year.

The benchmark and 93 risk management strategies were considered in this analysis for each of the three counties and for both crop year scenarios. Comparisons using means, downside risk as measured by the value-at-risk (VaR), and certainty equivalents (CEs) were made relative to the benchmark strategy as well as other management strategies.[5] Appropriate statistical tests were performed at the 5% significance level.

Strategies were initially ranked based on the mean net farm revenue per acre. The downside protection potential of risk management strategies was evaluated by calculating the net farm revenue associated with 5% VaR levels. Strategies with higher 5% VaR values provide better downside protection. CEs determine the amount that the decision maker would have to be paid to be indifferent between a particular risky alternative and a non-risky investment. A specific risky alternative is worth less for individuals with higher levels of risk aversion; thus the CE decreases as risk aversion increases.

CEs were determined using Pratt absolute risk-aversion coefficients assuming a power utility function (Richardson, 2001). Absolute risk-aversion coefficients were calculated using risk-aversion coefficients ranging between 0 (a risk-neutral individual) and 4 (a very risk-averse individual) and cash rent per acre as the measure of wealth. For the CE calculations, the regional cash rent (Dobbins and Cook, 2002) closest to the average corn yield generated in the model was used as the measure of wealth.

Data

Due to data availability, the years considered were 1986–2001 for Carroll and Elkhart counties and 1987–2001 for Posey County. Corn and soybean cash prices were gathered from a central, northern, and southern Indiana elevator (Hurt, 2002; Cabrini de Colonna, 2003). The harvest-time cash sales strategy involved selling all production at the harvest-time price. The harvest-time cash price was the weekly

[3] Historically, from 1975 to 2001, Carroll County corn and soybeans averaged 141.8 and 47 bushels per acre, respectively, with coefficients of variation of 15% and 14.3%. Elkhart corn yields averaged 123.5 bushels per acre with a 12.8% coefficient of variation, while soybeans averaged 41.5 bushels per acre and had a 9.5% coefficient of variation. Corn in Posey County averaged 132.4 bushels per acre with a coefficient of variation of 16.5%, while soybeans averaged 38.2 bushels per acre and had an 11.7% coefficient of variation.

[4] Years following a short crop year include 1989, 1992, 1994, and 1996. The limited number of observations was judged to preclude meaningful analysis of years following a short crop year.

[5] For a discussion of the concept and use of value-at-risk (VaR), see Manfredo and Leuthold (2001).

price closest to November 1 and October 1 of each year for corn and soybeans, respectively.

Corn and soybean futures and options prices were gathered from the Chicago Board of Trade (CBOT) and Collins (2001). Three futures prices were considered for each contract: an early spring futures contract price (March 15), a late spring futures contract price (June 1), and a harvest-time futures price for corn (November 1) and for soybeans (October 1). The nearest at-the-money contracts for the Wednesday closest to March 15, June 1, and October 1 or November 1 were used to determine option strike prices and option premiums. Similar to Pritchett et al. (2004), the springtime forward prices for harvest delivery were assumed to be $0.20 under the December corn and November soybean CBOT futures contract, respectively. The marketing year average prices in Indiana were obtained from the National Agricultural Statistics Service (NASS) and FCIC prices for corn and soybeans were collected from Collins (2001) and the National Crop Insurance Services (NCIS, 2000). Opportunity costs, commissions, and brokerage service fees were similar to those reported in Pritchett et al.

County-level yields were obtained from NASS. To calculate the 10-year moving yield average for APH, yield information from 1975–2001 was used for Carroll and Elkhart counties, and data from 1976–2001 were used for Posey County.

The model uses farm-level detrended yields for corn that were calculated from county detrended yield using a regression equation plus a stochastic error. Farm-level corn yields from 1985–1994 were obtained from an APH database through the Risk Management Agency (RMA). This database included 84, 8, and 9 farm-level yield observations for Carroll, Elkhart, and Posey counties, respectively. The corn farm-level regression equation coefficients and standard errors (in parentheses) are presented in equations (7)–(9), where t is the year and i is an index of farm observations.

For Carroll County farms:

$$(7)\quad \textit{Corn Detrended Yield}_{t,i} = \underset{(7.98)}{-16.74} + \underset{(0.05)}{1.27} \times (\textit{County Corn Detrended Yield}_t) + e_{i,1}.$$

For Elkhart County farms:

$$(8)\quad \textit{Corn Detrended Yield}_{t,i} = \underset{(33.97)}{35.15} + \underset{(0.25)}{0.74} \times (\textit{County Corn Detrended Yield}_t) + e_{i,1}.$$

For Posey County farms:

$$(9)\quad \textit{Corn Detrended Yield}_{t,i} = \underset{(14.97)}{-20.04} + \underset{(0.10)}{1.03} \times (\textit{County Corn Detrended Yield}_t) + e_{i,1}.$$

An empirical distribution of the errors based on equations (7)–(9) was used to compute farm-level detrended corn yields in each model iteration. Because farm-level soybean yields were not available, farm-level soybean detrended yields were estimated by the following equation in which the error term distribution was determined by a normal distribution of percentage errors from the county-level yield.

$$(10)\quad \textit{Farm Soybean Detrended Yield}_{t,i} = \textit{County Soybean Detrended Yield}_t + e_{i,2}.$$

Similar to Pritchett et al. (2004), the proportion of the difference in variability between county and farm detrended yields was assumed to be the same for both corn and soybean yields.[6]

Given the similarity in production environments, corn and soybean yields tend to be highly correlated. Correlations of corn and soybean county detrended yields during the period analyzed were 0.66, 0.56, and 0.65 for Carroll, Elkhart,

[6] For example, if the coefficients of variation of detrended county and farm corn yields are 14% and 21%, respectively, and the coefficient of variation of detrended county soybean yields is 10%, then the coefficient of detrended farm-level soybean yields would be 15%.

and Posey counties, respectively, all of which were significant at $p < 0.0001$.

Insurance premiums for APH, CRC, and RA were calculated based on the farm-level APH yield using the Continuous Rating Model (CRM). Insurance base premium rates for GRP, GRIP, and IP are determined from RMA actuarial tables. RA-BP and RA-HP insurance premium rates were obtained from the *RMA Premium Calculator* (USDA/RMA, 2002a). GRP insurance premiums and expected corn and soybean yields were generated by the GRP software (USDA/RMA, 1998) and actuarial tables (USDA/RMA, 2002b) from the RMA. Premium subsidies instituted for 2001 and later years were considered in the calculation of the premium paid by producers.

To simplify the evaluation of the effect of risk management strategies on net farm revenue, a number of assumptions were made. It was assumed that all of the corn and soybeans would each be treated as a basic unit for insurance purposes. All farm revenue and variable costs of risk management were accounted for each year. Payments that would not be collected during the crop year were discounted back to the end of the production period. For instance, indemnity payments for GRP and GRIP do not occur until NASS releases the county yields, generally in March of the year following harvest of the crop. An assumed 7% annual interest rate was used to discount the indemnities in order to reflect their cash value in December following the harvest.

Results

Following the procedures described, net farm revenues were simulated for the benchmark strategy and selected risk management strategies for each of the three counties and for both crop year scenarios: "all years" and "years following a normal crop year." First, the various types of insurance products are considered with different levels of hedging of expected production. Second, the effects of the all-years and years following a normal year crop year scenarios are quantified. Third, the effects of different forward pricing techniques and timing of pricing are explored. Finally, the effects of differences in the level of risk aversion on the certainty equivalents of selected strategies are analyzed.[7]

Insurances and Hedging

Table 1 summarizes the mean net farm revenues and 5% VaR levels for different crop insurance products and four levels of March 15 hedging of expected production for all three counties for the all-years scenario.[8] In Carroll County, all of the insurance products considered had mean net revenues per acre greater than the $353.42 of the no insurance benchmark at the zero hedging level. The increases in net revenues per acre ranged from about $1 for APH to about $15 for GRIP. These findings indicate that with the premium subsidies, the returns to insurance are positive for producers. All of the 5% VaR values for Carroll County were also greater than the $221.94 of the benchmark, indicating greater downside risk protection. These increases ranged from about $12 per acre for GRP to over $50 for CRC and IP. The magnitude of the differences in net revenues and 5% VaR values were similar across insurance types for all levels of hedging.

In Elkhart County, except for GRP, the mean net farm revenue per acre of various insurance products exceeded the $281.37

[7] Crop insurance strategies are referred to by the acronym of the product, level of price election or protection level, and coverage level. Marketing strategies are referred to by the instrument involved, date position is established, and percentage of expected production involved. More complete simulation results are available from the authors upon request.

[8] The 75% coverage levels of APH, CRC, and IP, and the 70% of maximum protection level of GRP and GRIP with 90% trigger yields were selected to reflect approximately equal levels of protection for a producer. Because of the similarity of RA and CRC, only CRC was considered.

Table 1. Mean Net Farm Revenue and 5% VaR Values ($/acre) for Selected Insurance Products and Levels of March 15 (M15) Hedging for the All-Years Scenario

Hedge Level (% of Expected Production)	Futures (M15)	Futures (M15) Combined With: APH (100%PE) 75%	CRC 75%	IP 75%	GRP (70%MP) 90%	GRIP (70%MP) 90%
			— CARROLL COUNTY —			
0	353.42	354.54	358.01	359.53	357.38	368.45
	(221.94)	(247.88)	(273.21)	(274.01)	(233.64)	(244.96)
33	365.84	366.96	370.43	371.95	369.80	380.87
	(231.42)	(263.35)	(284.13)	(281.96)	(246.75)	(250.82)
66	378.93	380.05	383.52	385.04	382.89	393.96
	(233.44)	(272.06)	(284.82)	(278.96)	(255.50)	(256.55)
100	392.74	393.85	397.32	398.85	396.70	407.76
	(240.65)	(273.90)	(285.71)	(277.87)	(264.48)	(262.28)
			— ELKHART COUNTY —			
0	281.37	283.19	286.72	291.24	279.99	283.11
	(152.42)	(189.56)	(209.40)	(214.05)	(152.19)	(158.71)
33	291.02	292.84	296.37	300.89	289.65	292.76
	(164.04)	(201.62)	(215.87)	(218.47)	(161.14)	(164.25)
66	300.67	302.49	306.02	310.54	299.30	302.41
	(172.96)	(206.60)	(217.89)	(219.84)	(170.31)	(168.64)
100	311.70	313.52	317.06	321.57	310.33	313.44
	(177.66)	(211.16)	(221.31)	(222.23)	(176.35)	(176.16)
			— POSEY COUNTY —			
0	274.30	269.27	269.33	273.57	275.17	284.60
	(197.57)	(197.22)	(210.29)	(214.32)	(203.92)	(208.86)
33	286.33	281.30	281.36	285.60	287.21	296.62
	(208.19)	(207.36)	(218.12)	(222.19)	(214.63)	(214.09)
66	298.36	293.33	293.39	297.63	299.24	308.65
	(215.58)	(216.14)	(223.84)	(227.78)	(224.24)	(219.73)
100	309.39	304.35	304.41	308.65	310.26	319.68
	(222.83)	(224.42)	(227.47)	(231.62)	(231.35)	(223.95)

Note: Values in parentheses are 5% VaR.

of the benchmark no insurance strategy. The mean net farm revenue for GRP was about $1 less per acre than the benchmark, while APH and GRIP were about $2 higher and IP was about $10 per acre higher. The 5% VaR levels, again with the exception of GRP, were also consistently higher than the benchmark strategy, and CRC and IP had the highest 5% VaR levels.

In Posey County, the individual farm-based APH, CRC, and IP products all had mean net farm revenues that were less than the benchmark strategy—about $5 per acre less for APH and CRC and about $1 less for IP. Although the coefficients of variation for the detrended farm-level yields were lower in Posey County than other counties, premium rates per bushel of expected production were substantially higher than in Carroll and Elkhart counties. The 5% VaR values for APH and the benchmark were virtually identical, while CRC and IP had higher VaR values indicating that farm-based insurances did provide some downside risk protection in Posey County. Net revenues and 5% VaR values of the county-based GRP and GRIP were both higher than the benchmark strategy.

Table 2. Mean Net Farm Revenue and 5% VaR Values ($/acre) for Different Levels of Hedging in Carroll, Elkhart, and Posey Counties Under the 2 Scenarios: All-Years and Years Following a Normal Crop Year

Hedge Level (% of Expected Production)	CARROLL COUNTY		ELKHART COUNTY		POSEY COUNTY	
	All Years	Following Normal Year	All Years	Following Normal Year	All Years	Following Normal Year
0	353.42	344.70	281.37	282.11	274.30	264.68
	(221.94)	(220.38)	(152.42)	(153.42)	(197.57)	(193.68)
33	365.84	352.85	291.02	288.06	286.33	273.80
	(231.42)	(222.90)	(164.04)	(159.57)	(208.19)	(200.38)
66	378.93	360.67	300.67	294.00	298.36	282.92
	(233.44)	(225.81)	(172.96)	(165.15)	(215.58)	(208.04)
100	392.74	369.93	311.70	301.06	309.39	291.27
	(240.65)	(229.55)	(177.66)	(169.86)	(222.83)	(216.00)

Note: Values in parentheses are 5% VaR.

The unexpected result observed in Table 1 is the higher net revenues associated with the higher levels of March 15 hedging. This finding is consistent with the Wisner, Blue, and Baldwin (1998) hypothesis of pre-harvest marketing of grains increasing returns for producers, and also supports some of the results reported by Hagedorn et al. (2005). Hedging higher levels of expected production increased both net revenues per acre and the 5% VaR values in all three counties. For example, in Carroll County, hedging 100% of expected production on March 15 increased net revenue about $39 per acre and increased the 5% VaR by about $19 per acre. Effects were similar, but of smaller magnitude because of the lower crop yields, in both Elkhart and Posey counties. These effects occurred for all types of insurances considered.

In Table 2, mean net revenues and 5% VaR values are compared for the all-years and years following a normal crop year scenarios for different levels of hedging for the three counties. The magnitude of the impacts of higher levels of hedging were reduced, but are not eliminated in the years following a normal crop year scenario. Mean returns with no hedging were reduced about $10 per acre in Carroll and Posey counties. In Elkhart County, mean net revenue without hedging was slightly higher following a normal crop year. At higher levels of hedging, the differences between the scenarios increased, with reductions of mean net revenue of nearly $23 per acre in Carroll County, $18 in Posey County, and nearly $11 in Elkhart County when 100% of expected production is hedged. The 5% VaR values were also consistently reduced at all levels of hedging, but the reductions were smaller than for mean net revenues.

Methods and Timing

Table 3 presents the mean net revenues and 5% VaR values associated with some alternative methods and times of forward pricing. Hedging on March 15 provides the highest mean net returns and 5% VaR values of the strategies considered in Carroll and Elkhart counties for both scenarios and following normal years in Posey County. A slightly different historical time period was considered in Posey County and puts had a slightly higher net return than futures, but lower 5% VaR value for the all-years scenario. Cash-forward contracting on March 15 provided higher net returns than options positions established on March 15 for four of the six situations considered. However, the 5% VaR values were substantially lower with forward contracting on March 15 in Carroll and Posey counties.

Table 3. Mean Net Farm Revenue and 5% VaR Values ($/acre) for Selected Times and Methods of Pre-Harvest Pricing Under the 2 Scenarios: All-Years and Years Following a Normal Crop Year

	CARROLL COUNTY		ELKHART COUNTY		POSEY COUNTY	
Strategy	**All Years**	**Following Normal Year**	**All Years**	**Following Normal Year**	**All Years**	**Following Normal Year**
Benchmark	353.42	344.70	281.37	282.11	274.30	264.68
	(221.94)	(220.38)	(152.42)	(153.42)	(197.57)	(193.68)
Futures (M15) 100%	392.74	369.93	311.70	301.06	309.39	291.27
	(240.65)	(229.55)	(177.66)	(169.86)	(222.83)	(216.00)
Puts (M15) 100%	363.70	351.01	291.82	289.34	312.17	273.68
	(223.92)	(219.74)	(160.03)	(156.69)	(209.77)	(202.65)
Forward (M15) 100%	371.47	348.70	304.42	294.21	292.28	275.21
	(191.63)	(180.78)	(163.96)	(156.73)	(199.59)	(192.96)
Forward (J1) 100%	348.65	329.72	286.80	279.69	270.35	254.86
	(195.39)	(181.83)	(151.94)	(143.45)	(183.83)	(176.45)
APH (100%PE) 75%	380.05	362.55	302.49	296.00	293.33	278.53
Futures (M15) 66%	(272.06)	(265.23)	(206.60)	(202.69)	(216.14)	(211.90)
APH (100%PE) 75%	364.21	349.28	290.58	286.07	297.31	265.43
Futures (J1) 66%	(256.31)	(252.87)	(195.94)	(190.18)	(204.22)	(197.77)

Note: Values in parentheses are 5% VaR.

Delaying forward pricing until June 1 resulted in sharply lower mean net revenues as compared with similar strategies executed on March 15 in all three counties. For cash-forward contracting, net revenues were reduced about $23 per acre in Carroll County in the all-years scenario and about $19 in the years following a normal crop year scenario. Both net revenues and the 5% VaR values were below those of the benchmark strategy. Similar reductions in net revenue and 5% VaR values occurred in Elkhart and Posey counties with outcomes in three of four cases below the benchmark strategy. When hedging 66% of expected production with futures was combined with APH insurance at the 75% coverage level, delaying taking a futures position from March 15 to June 1 resulted in both lower net revenues ($10 per acre or more) and lower 5% VaR values in Carroll and Elkhart counties. Lower 5% VaR values were associated with positions established on June 1 in Posey County, although results for mean net revenues were mixed. These results highlight the importance of timing of pre-harvest pricing.

Certainty Equivalents

Table 4 summarizes the CEs per acre for the benchmark strategy and three of the top-ranked risk management strategies in each county for four levels of relative risk aversion under both crop year scenarios.[9] The CE of a strategy, the certain amount an individual would accept for a risky alternative, decreases as the relative risk aversion of a producer increases. The decreases in the CE for the all-years benchmark strategy between a risk-neutral and highly risk-averse producer (relative risk-aversion levels of 0 and 4, respectively) were over $43 in Elkhart County, about $27 in Carroll County, and about $17 in Posey County. The CEs of the benchmark strategy for the all-years scenario were about $10 higher than the years following a normal crop year scenario in Posey County and $7 to $9 higher in Carroll County, while the CEs of the two scenarios were nearly the same for Elkhart County.

[9]The 94 strategies considered have a variety of combinations of strategies but do not include all of the possible strategies that could be specified.

Table 4. Certainty Equivalents of Benchmark and Top 3 Risk Management Strategies Under the 2 Scenarios: All-Years and Years Following a Normal Crop Year ($/acre)

PANEL A. CARROLL COUNTY, All-Years Scenario

Strategy Rank	Risk Management Strategies and CEs for Relative Risk-Aversion Levels			
	0	1	2	4
	Benchmark $353.42	Benchmark $347.32	Benchmark $340.81	Benchmark $326.25
1	GRIP (70%MP) 90% Futures (M15) 100% $407.76	GRIP (70%MP) 90% Futures (M15) 100% $400.66	GRIP (70%MP) 90% Futures (M15) 100% $393.06	IP 75% Futures (M15) 100% $378.97
2	IP 75% Futures (M15) 100% $398.85	IP 75% Futures (M15) 100% $393.88	IP 75% Futures (M15) 100% $388.90	CRC 75% Futures (M15) 100% $378.62
3	CRC 75% Futures (M15) 100% $397.32	CRC 75% Futures (M15) 100% $392.57	CRC 75% Futures (M15) 100% $387.87	GRIP (70%MP) 90% Futures (M15) 100% $375.96

PANEL B. ELKHART COUNTY, All-Years Scenario

Strategy Rank	Risk Management Strategies and CEs for Relative Risk-Aversion Levels			
	0	1	2	4
	Benchmark $281.37	Benchmark $272.47	Benchmark $262.43	Benchmark $238.00
1	IP 75% Futures (M15) 100% $321.57	IP 75% Futures (M15) 100% $316.34	IP 75% Futures (M15) 100% $311.07	IP 75% Futures (M15) 100% $300.51
2	CRC 75% Futures (M15) 100% $317.06	CRC 75% Futures (M15) 100% $311.93	CRC 75% Futures (M15) 100% $306.81	CRC 75% Futures (M15) 100% $296.68
3	APH (100%PE) 75% Futures (M15) 100% $313.52	APH (100%PE) 75% Futures (M15) 100% $307.47	APH (100%PE) 75% Futures (M15) 100% $301.40	IP 75% Futures (M15) 66% $291.54

PANEL C. POSEY COUNTY, All-Years Scenario

Strategy Rank	Risk Management Strategies and CEs for Relative Risk-Aversion Levels			
	0	1	2	4
	Benchmark $274.30	Benchmark $269.83	Benchmark $265.46	Benchmark $257.10
1	GRIP (70%MP) 90% Futures (M15) 100% $319.68	GRIP (70%MP) 90% Futures (M15) 100% $314.26	GRIP (70%MP) 90% Futures (M15) 100% $308.78	GRIP (70%MP) 90% Futures (M15) 100% $297.69
2	Put (M15) 100% $312.16	GRP (70%MP) 90% Futures (M15) 100% $305.74	GRP (70%MP) 90% Futures (M15) 100% $301.31	GRP (70%MP) 90% Futures (M15) 100% $292.72
3	GRP (70%MP) 90% Futures (M15) 100% $310.26	Futures (M15) 100% $304.32	IP 75% Futures (M15) 66% $299.94	IP 75% Futures (M15) 66% $291.83

Table 4. Extended

PANEL A. CARROLL COUNTY, Years Following a Normal Year Scenario

Strategy Rank	Risk Management Strategies and CEs for Relative Risk-Aversion Levels			
	0	1	2	4
	Benchmark $344.70	Benchmark $338.91	Benchmark $332.82	Benchmark $319.57
1	GRIP (70%MP) 90% Futures (M15) 100% $382.26	GRIP (70%MP) 90% Futures (M15) 100% $376.31	GRIP (70%MP) 90% Futures (M15) 100% $369.94	CRC 75% Futures (M15) 100% $358.87
2	GRP (70%MP) 90% Futures (M15) 100% $376.73	GRP (70%MP) 90% Futures (M15) 100% $371.70	IP 75% Futures (M15) 100% $366.95	IP 75% Futures (M15) 100% $358.86
3	IP 75% Futures (M15) 100% $375.11	IP 75% Futures (M15) 100% $371.02	GRP (70%MP) 90% Futures (M15) 100% $366.37	GRIP (70%MP) 90% Futures (M15) 100% $355.65

PANEL B. ELKHART COUNTY, Years Following a Normal Year Scenario

Strategy Rank	Risk Management Strategies and CEs for Relative Risk-Aversion Levels			
	0	1	2	4
	Benchmark $282.11	Benchmark $272.94	Benchmark $262.57	Benchmark $237.37
1	IP 75% Futures (M15) 100% $308.89	IP 75% Futures (M15) 100% $303.67	IP 75% Futures (M15) 100% $298.45	IP 75% Futures (M15) 100% $288.14
2	CRC 75% Futures (M15) 100% $304.60	CRC 75% Futures (M15) 100% $299.49	CRC 75% Futures (M15) 100% $294.43	CRC 75% Futures (M15) 100% $284.53
3	APH (100%PE) 75% Futures (M15) 100% $303.05	APH (100%PE) 75% Futures (M15) 100% $297.10	IP 75% Futures (M15) 66% $291.73	IP 75% Futures (M15) 66% $281.92

PANEL C. POSEY COUNTY, Years Following a Normal Year Scenario

Strategy Rank	Risk Management Strategies and CEs for Relative Risk-Aversion Levels			
	0	1	2	4
	Benchmark $264.68	Benchmark $260.48	Benchmark $256.40	Benchmark $248.58
1	GRIP (70%MP) 90% Futures (M15) 100% $299.37	GRIP (70%MP) 90% Futures (M15) 100% $294.98	GRIP (70%MP) 90% Futures (M15) 100% $290.54	GRIP (70%MP) 90% Futures (M15) 100% $281.55
2	GRP (70%MP) 90% Futures (M15) 100% $293.88	GRP (70%MP) 90% Futures (M15) 100% $290.17	GRP (70%MP) 90% Futures (M15) 100% $286.54	GRP (70%MP) 90% Futures (M15) 100% $279.52
3	Futures (M15) 100% $291.27	IP 75% Futures (M15) 66% $287.79	IP 75% Futures (M15) 66% $284.46	IP 75% Futures (M15) 66% $278.22

This similarity of CEs in Elkhart County appears to be due to its greater downside risk, because the differences among CE values decreased for different levels of risk aversion when risk management strategies were implemented.

Given the previous results, it is not surprising that the top-ranked strategies for all counties involve establishment of futures or options positions on March 15 for 100% of expected production combined with crop insurance products in both scenarios. For the risk-neutral producer, the top-rated risk management strategy had a $40 to $54 per acre higher CE than the benchmark strategy in the all-years scenario. The CEs of these strategies following a normal crop year are reduced relative to the all-years scenario by about $20 to $26 in Carroll County, $16 to $20 in Posey County, and by $12 to $13 in Elkhart County. These findings reveal that the returns to aggressive early spring marketing are reduced, but are not eliminated, by excluding the years following a short crop year.

In all three counties, as the level of relative risk aversion increases, IP insurance tends to be incorporated into the risk management strategies with the highest CEs. Again, there is little difference in the top-ranked strategies between the crop year scenarios.

In Carroll County, there was a tendency for a shift away from the county-based GRP and GRIP insurance toward the farm-based CRC and IP insurances as the level of risk aversion increased. Because indemnities with CRC and IP should correspond more closely than GRP and GRIP to a producer's experience, this shift is not unexpected. This shift occurred in both crop year scenarios.

In Elkhart County, none of the top-ranked risk management alternatives included the county-based GRP or GRIP insurances. The all-years CE for GRP with 70% maximum of the protection level, 90% coverage level, and futures contracting 66% of expected production on March 15 was $280.65 for an Elkhart County producer with a relative risk-aversion level of 2, about $21 less than the third ranked strategy in Table 4. The county-based GRP and GRIP insurance products provide less downside protection for losses than the farm-based insurance products in Elkhart County.

In contrast to Elkhart County, for Posey County APH insurance was not in the top-ranked alternatives. As noted previously, per bushel premium costs of APH insurance in Posey County were nearly double those of Carroll and Elkhart counties. However, the all-years CE for APH insurance at the 75% level with futures contracting of 66% of expected production on March 15 was about $284 per acre for a Posey County producer with a relative risk-aversion level of 2. This strategy ranked 17th overall, with a net revenue about $20 less than the third ranked alternative in Table 4.

Conclusions and Implications

A benchmark and 93 risk management strategies were considered in Carroll, Elkhart, and Posey counties of Indiana. A variety of risk management strategies involving marketing, crop insurance products, and combinations of marketing and insurance strategies were considered. To determine if market conditions, which can be observed by producers, affect the level and variability of net farm revenue of risk management strategies, two scenarios were evaluated. The first scenario included "all years" in the study period, while the second was restricted to the "years following a normal crop year."

Many of the 93 risk management strategies considered outperformed the benchmark strategy of no insurance and cash sale at harvest, although only the top-ranked strategies are discussed in the results. For Carroll County, in the all-years scenario, the benchmark strategy ranked 87th for mean income, 79th for the 5% VaR value, and 87th in terms of CE for a relative risk-aversion level of 2.

In Elkhart County, the benchmark strategy in the all-years scenario ranked 77th, 81st, and 78th for mean income, 5% VaR, and CE, respectively. For Posey County, in the all-years scenario, the benchmark ranked 61st for mean income, 72nd for 5% VaR, and 64th for CE. These rankings changed relatively little if only the years following a normal crop year were considered. For example, for a relative risk-aversion level of 2, the CEs of the benchmark strategies ranked 80th, 71st, and 63rd in Carroll, Elkhart, and Posey counties, respectively.

For both scenarios and all three counties, futures hedges established in March, in combination with insurance, provided the highest CEs among the risk management strategies evaluated. Establishment of positions in March resulted in higher returns and CEs than similar positions established in June. Higher CEs were also obtained when higher percentages of the expected production were hedged. These findings are consistent with the Wisner, Blue, and Baldwin (1998) hypothesis of pre-harvest marketing of grains increasing returns for producers and the Hagedorn et al. (2005) observation that the highest prices for corn and soybeans tended to be in the pre-harvest and harvest marketing windows. Considering only years following a normal crop year substantially reduced the returns associated with early marketing of corn and soybeans. However, these early spring marketing strategies still had the highest CE values of the alternatives considered. A partial explanation as to why these results are not consistent with the efficient market hypothesis may be the limited number of years in the analysis.[10]

Further research should be conducted to analyze whether the higher returns associated with these early marketing strategies are confirmed. If these returns to early pricing are confirmed, it suggests producers should use much more aggressive marketing strategies than most producers currently would be willing to consider. It is likely that an extensive marketing education program would be needed to make producers aware of the potential for increased net returns and to change their marketing behavior. However, as Tomek and Peterson (2005) caution, "If grain markets in the United States are semistrong form efficient, then recommendations based on seeming market inefficiencies have little validity" (p. 1263).

There are differences in the effectiveness of risk management alternatives among geographical areas in Indiana.[11] APH insurance was not included in the highly ranked strategies for Carroll and Posey counties, and GRP and GRIP were not included among the highly ranked strategies in Elkhart County. As noted previously, the downside risk in Elkhart County appears greater than in other areas, even if risk management strategies are implemented and the county-based insurances provide less protection to producers. In Posey County, the coefficients of variation of farm-level yields are the lowest of the counties analyzed, but the premium rates per bushel of expected production are approximately double the other counties studied and may merit review by the FCIC.

Under both scenarios in Carroll and Elkhart counties, there tended to be a shift away from futures contracts alone as the level of producer's risk aversion increased. This shift tended to occur at lower levels of risk aversion in the years following a normal crop year scenario. Thus, the prior crop year and the risk-aversion level of a producer do affect the

[10] As noted previously, the apparent gains to early spring pricing may be the result of the period of analysis and should not be construed as generating a positive return each year.

[11] There are substantial differences in performance of insurance products across counties, and there is no "one-size-fits-all" strategy. Specific local conditions, as well as provisions of the insurance products that were not included in this analysis (e.g., optional units, prevented planting, and replant coverage), should be taken into consideration when choosing an insurance product.

effectiveness of risk management strategies. Although the CEs were lower when the analysis was restricted to years following a normal crop year, there were only small changes in the rankings of the risk management alternatives. Future research should include additional systematic marketing strategies combined with insurance and cover a broader array of both geographical locations and crops.

In summary, there are many risk management strategies that have higher CEs than the benchmark strategy of no insurance with cash sale at harvest in all three counties under both scenarios. There are many risk management strategies that outperformed the benchmark strategy but did not perform as well as the top-ranked strategies that were discussed in the results. Often the differences in CEs among these strategies are relatively small.

Differences do exist in the effectiveness of risk management alternatives among geographical areas, risk-aversion level of a producer, and prior crop year. However, results of the type that typically would be used for producer-oriented risk management educational programs do not appear to be especially sensitive to the prior crop year. There are a large number of risk management strategies with similar levels of performance that can increase mean returns and reduce downside risk. Consequently, for many producers in areas similar to those analyzed, it may be more important to implement some type of risk management strategy than attempt to identify the best strategy.

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Buying Stock in Value-Added Companies: An Alternative Choice for Vertical Diversification?

Joshua D. Detre, Christine A. Wilson, and Allan W. Gray

Abstract

Recent research has indicated that livestock producers who want to manage risk and diversify their operations should invest in the stock market. This research evaluates whether or not a portfolio of publicly held companies that are first handlers of pork products would provide pork producers with a means of enhancing annual returns and reducing the volatility in the annual returns. Ex ante results suggest producers can gain from investment in value-added stocks. Ex post results, however, imply producers must choose active management of their portfolio to receive the same type of benefits as the ex ante portfolio.

Key words: investment, risk management, stock market, value-added, vertical diversification, vertical integration

Structural change in the pork industry has caused the annual returns to farrow-to-finish hog operations to become highly volatile and has challenged pork producers to find new ways to reduce the annual volatility of these returns. One method for reducing the risk in their operations is to capture some of the profit associated with the value-added activities taking place beyond the farm gate. The additional profit available from value-added activities has arisen because consumers are no longer content with a non-uniform bulk product; instead, they want a consistent and uniform pork product. Since the activities that generate value-added profits typically occur beyond the farm gate, there is considerable interest among pork producers in finding ways to vertically integrate into pork processing (Buhr, 2002).

As noted by Buhr (2002), there are two mechanisms to accomplish the goal of vertical integration: (*a*) direct investment in the physical facilities of processing plants, and (*b*) investment in publicly traded companies that process pork products. Traditionally, vertical coordination is accomplished via ownership integration (direct investment into nonfarm holdings that process farm products, often through New Generation Cooperatives) or contractual agreements (marketing strategies). There are many risks inherent in these traditional means of vertical coordination including imperfect information sharing among vertical partners, contractual fallout (either party fails to uphold its side of the contract), and the shifting of management decisions from the farmer to the integrator.

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The question becomes: What benefits does the stock market offer that other methods of vertical coordination do not? Torgerson (2000) and Harris, Stefanson, and Fulton (1996) caution that there are problems associated with New Generation Cooperatives (NGCs). The up-front or initial equity investment may be substantial depending on the processing facility; the cost of these investments is typically between $10,000–$12,000 for access to marketing rights (Coltrain, Barton, and Boland, 2003; Sporleder and Zeuli, 2000). Farmers may find it difficult to raise the up-front capital funds required to purchase the initial shares in the NGC (Coltrain, Barton, and Boland, 2003). In contrast, although investment in the stock market requires a capital outlay, it is often accomplished on a smaller scale and does not have a predetermined investment amount.

Additionally, the initial investment in an NGC must be paid when the NGC is formed, while money may be invested at any time in the stock market and in any amount as long as the amount is sufficient to purchase a share of a security or mutual fund. Moreover, if the NGC chooses to expand, members must make another immediate investment if they want to have access to the additional capacity, whereas additional investment in a stock is not required if new shares are made available to the public (Coltrain, Barton, and Boland, 2003).

The ability of a farmer to purchase shares in the NGC and sell those shares to others is subject to board approval. This process limits the liquidity of the share, while the only limitation on selling and purchasing shares in the stock market is that the purchaser of the shares has sufficient funds to cover the purchase price of the shares (Coltrain, Barton, and Boland, 2003).

Additional benefits of the stock market as an investment tool include not having to hire new employees or management, not having to purchase new facilities or equipment, and not relying on the development of new products (product differentiation) or having to acquire a new customer base (Siebert, Jones, and Sporleder, 1997). In essence, by investing in the market, the farmer is investing in companies whose management, customer base, and capital structure are already in place. Furthermore, the costs associated with using the stock market are limited to the cost of purchasing the stock, the time managing the portfolio, and, if a producer so chooses, the cost of an investment broker. The cost and time management are conceivably much less than those of traditional vertical integration through expansion beyond the farm gate.

Siebert, Jones, and Sporleder (1997) state that the risks associated with stock market investment over the traditional integration investments are lessened by an assortment of factors, including the ability to invest in firms that operate in different geographic locations, the ability to invest in firms that function in one of the many markets associated with the commodity, and the high liquidity offered by publicly traded stocks.

Investments in the stock market do not suffer from the problem of asset specificity, which can affect investments in physical assets such as processing plants. It can be very difficult for farmers to sell their part of a processing facility because they are bounded by geographic region, approval of boards of directors, and often occupation. However, investors have the opportunity to sell shares in the market very quickly if they want either to get out of the market or to rebalance their portfolios, with little regard to where the buyers of the shares live or what they do for a living.

Clearly, the aforementioned benefits of a vertical diversification strategy based on investing in value-added stocks over traditional vertical diversification highlight the need for quantitative analysis to provide evidentiary support that investment in value-added stocks is a viable vertical diversification strategy for pork producers.

Toward that end, the primary objective of the research is to investigate the potential of a value-added portfolio consisting of investments in a farrow-to-finish operation and publicly traded value-adding processing companies as a source of vertical diversification.

Specifically, we pose the question: Will investment in these stocks reduce the annual volatility of returns and improve annual returns relative to investing strictly in the farrow-to-finish enterprise? Thus, the following hypothesis is proposed: By investing in a value-added portfolio, producers will benefit through an increase in reward (returns) for the amount of risk they bear in their overall portfolios. The goal is to provide producers with information on the use of investments in publicly traded companies as an alternative to direct investment in processing facilities as a strategic investment strategy for managing risk and increasing returns in the farrow-to-finish operation.

Previous Research

Vertical Diversification Using Nonfarm Financial Assets

Farmers are more likely to include off-farm assets as part of their overall portfolio when the farm operation does not produce multiple commodities, when they have a need to increase their portfolio's holding of liquid assets, when government support of their operation is small, and when on-farm returns are highly variable (Mishra and Morehart, 2001; Serra, Goodwin, and Featherstone, 2004). The above characteristics accurately describe farrow-to-finish operations in the United States. Previous research has examined the benefits offered to agricultural producers through investment in the stock market as a means of diversification (e.g., Betubiza and Leatham, 1994; Siebert, Jones, and Sporleder, 1997; Jones, Fulton, and Dooley, 1999; Duval and Featherstone, 2002; Buhr, 2002).

First, Betubiza and Leatham (1994) examine the impacts of including a broad market mutual fund as part of a farmer's overall portfolio using discrete stochastic programming. The mutual fund in their portfolio mimics the universe of stocks available for investment; therefore, it serves as a vehicle for accomplishing traditional diversification as opposed to vertical diversification into stocks of companies who process a farmer's commodity. The authors conclude the mutual fund used in their study enhances a farmer's income level and the stability of the income. In essence, broad market diversification into a mutual fund is both risk reducing and mean enhancing in terms of farm income.

Studies by Duval and Featherstone (2002) and Buhr (2002) both rely on a mean-variance approach (which is also adopted in our paper) for developing farm investment portfolios. Duval and Featherstone develop a fuzzy logic method for evaluating farmers' investment portfolios by characterizing their risk preferences. The primary purpose of their research was to develop a methodology to shift the decision process to individual investors for choosing an optimal portfolio of assets.

Extending the work of Duval and Featherstone, Buhr (2002) employs a mean-variance methodology by examining the returns to a specific operation (hogs), as opposed to aggregate farm returns. Doing so allows him to examine more directly the impacts of true vertical diversification, i.e., investment in firms that process hogs. Buhr points out that the research conducted by Siebert, Jones, and Sporleder (1997) relies on an ad hoc methodology of a vesting goal where the vesting amount is a proportion of physical production; further, the analyses of Duval and Featherstone (2002) and Siebert, Jones, and Sporleder (1997) both utilize aggregate farm returns. Buhr contends these methods make it difficult to determine if investment is attributed to broad market diversification (as with Betubiza and Leatham, 1994) or if the results can be attributed to true vertical diversification.

Contribution to the Literature

The results reported by the studies cited above indicate the stock market is a viable investment vehicle for an agricultural producer for both broad market diversification and vertical diversification; however, each new piece of research raises additional questions. Our study furthers the literature by building upon the work of earlier investigations in four major areas:

- Previous works generate an EV frontier, which contains multiple optimal portfolios. To determine the optimal portfolio on the EV frontier for an individual farmer requires knowledge of the farmer's risk-aversion level. The value-added portfolios constructed in this paper will be optimal for all risk-averse investors regardless of their level of risk aversion.

- Earlier works maintain a static set of stock investment opportunities, while this study updates the stock investment opportunities by allowing stocks to come in and out of the investment universe. Thus, prior research examines only the effects of value-added stocks on a farmer's portfolio one time. Evensky (1997) suggests portfolios should be rebalanced to adjust for new information that might make the current portfolio suboptimal. We follow his approach of rebalancing on a calendar basis and develop a portfolio for each of the years from 1979–2001. This approach allows for the examination of how a producer's portfolio has changed over time. Specifically, we can examine any change in benefits which occur throughout time in terms of vertical diversification, change in the makeup of companies included in the portfolio, and the amount of investment allocated to the stocks and to the farrow-to-finish operation.

- The research presented in this paper employs a forecasting model, a feature not used in prior literature.

- Finally, this paper examines whether the optimal value-added portfolio can outperform the returns to the farrow-to-finish-only portfolio on an ex post basis, whereas previous studies examine the benefits of a value-added portfolio on a single ex ante basis only.

Model and Methodology

Portfolio Theory

Theoretical Framework

As with Buhr (2002), the conceptual model for this work is based on Markowitz's (1952) portfolio which produces an efficient frontier of investments. We recognize there is only one point on the Markowitz "efficient frontier" of risky assets that is relevant to the investment decision with the inclusion of a riskless asset—the portfolio occurring at the point of tangency, point B, in Figure 1. The tangent portfolio is the optimum unlevered portfolio that occurs with a given riskless rate of return when the economic decisions are separated from the financing decisions (Lintner, 1965; Levy and Sarnat, 1984).[1]

The pork producer's wealth and risk aversion determine the relevant amount of each dollar invested in the risky assets (value-added stocks and the farrow-to-finish operation) and the proportion of the producer's portfolio allocated to the risk-free asset. Furthermore, it should be noted that the optimal mix of risky stocks does not change with the pork producer's wealth and risk aversion; only the proportion of the portfolio allocated to these assets changes. In Figure 1, for any portfolio that lies on the line between points R_f and B, the producer is lending at the risk-free rate, and for any portfolio that lies on the line extending beyond point B,

[1] This result is known as the separation theorem, which suggests that all investors will have the same proportionate composition of stocks in their portfolio regardless of their utility function (Elton et al., 2003; Ait-Sahalia and Hansen, 2005; Campbell and Viceira, 2002; Fama and French, 2004).

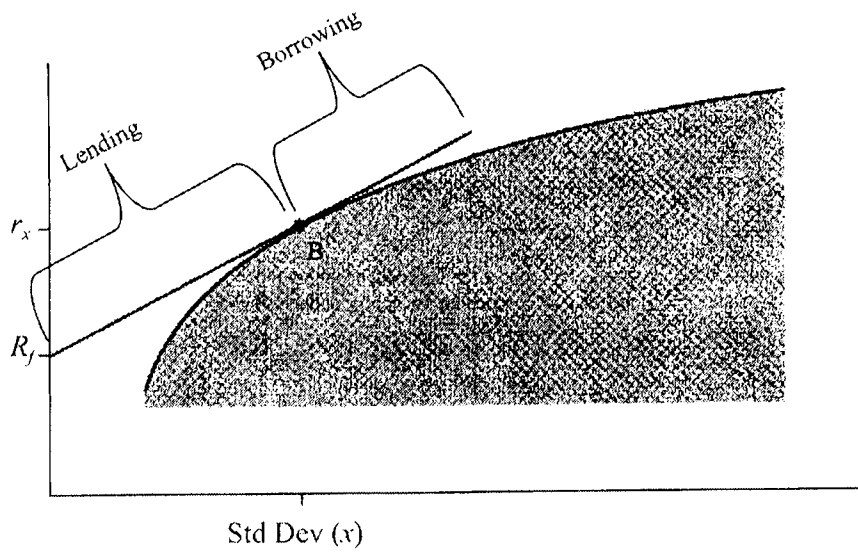

Figure 1. Graphical Representation of the Sharpe Ratio

the producer is borrowing at the risk-free rate (Elton et al., 2003).[2]

This portfolio is formed by finding the optimal mix of value-added stocks and the farrow-to-finish operation providing the highest forecasted Sharpe ratio. The Sharpe ratio determines the portfolio that generates the best return per unit of risk for a given risk-free interest rate for a single portfolio of risky assets. This portfolio is preferred to all other portfolios (Tobin, 1958; Sharpe, 1963, 1964, 1966; Lintner, 1965; Elton et al., 2003; McLeish, 2005).

Empirical Methods

Figure 2 diagrams and summarizes the major steps of the methodology presented in this paper. The empirical steps are: (*a*) calculate historical investment returns, (*b*) test the correlation of the returns, (*c*) forecast returns using ARMA and ARIMA models, (*d*) stochastically simulate returns, (*e*) develop and describe different portfolio scenarios, (*f*) optimize the forecasted Sharpe ratio for each ex ante scenario, and (*g*) ex post test the optimized portfolios.

The optimal portfolios in this analysis are determined via an optimization model that generates thousands of states of nature using stochastic simulation in a manner whereby correlations are maintained across investments, thus assuming serial independence of returns for each of the years 1974–2001.[3] The values used in the stochastic simulation are based on the error terms, the coefficients, and the forecasted values from an ARMA (1, 1) model for the stock returns and an ARIMA (1, 1) model for the farrow-to-finish returns.

[2] Financing is a key tool in achieving optimal investment performance because borrowing and lending serve as the means for allowing investors to determine their risk classes (Modigliani and Modigliani, 1997). The choice of levering or unlevering the portfolio also affects the expected return and the expected risk of the portfolio. If an investor unlevers (levers) a certain percentage of the portfolio to buy some of the riskless asset, then the investor's return will decrease (increase) the returns of the portfolio by that percentage and the dispersion of the returns will decrease (increase) by that percentage (Modigliani and Modigliani).

[3] Portfolio problems, such as the one in this study, are often solved as mathematical programming problems using various computing packages (Elton et al., 2003) with results equivalent to those produced by the methodology used here (Jackson and Staunton, 1999; Winston, 2001).

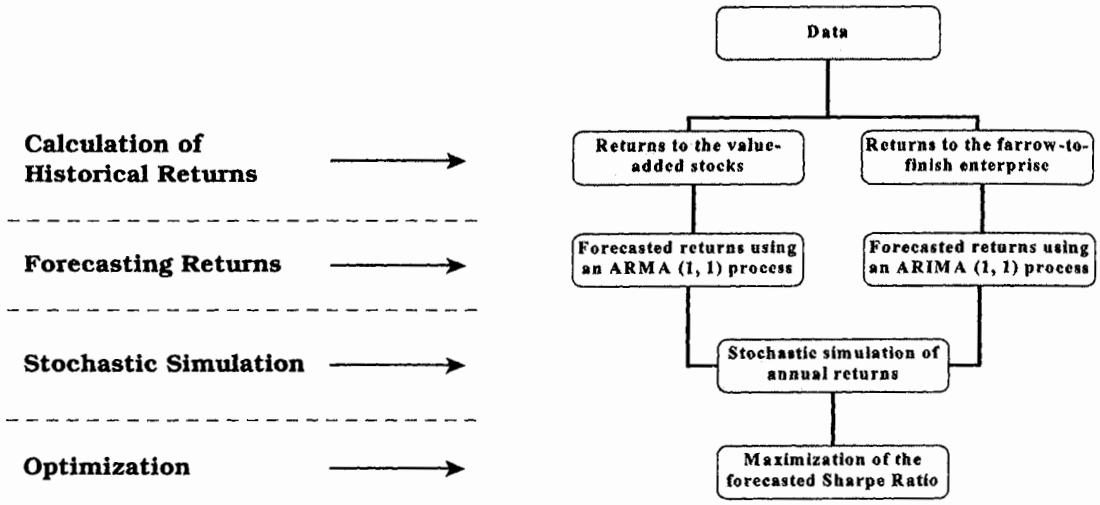

Figure 2. Flow Chart of the Methodology

The set of correlated stochastic annual returns is used to develop a weighted portfolio that maximizes the forecasted Sharpe ratio. Maximization of this ratio is accomplished by choosing the mix of investments in a portfolio having the best return per unit of risk. This maximization is done prior to knowing the outcome for the particular year's returns. Consequently, the optimal portfolio may underperform or outperform the returns to farrow-to-finish investments only. The following sections describe in detail the process and empirical methods used to generate the optimal portfolios.

Investment Returns Data

The first step in developing optimal portfolios was determining the data and calculating the investment returns. Data for this research consist of monthly returns from January 1974 to December 2001 for farrowing and finishing hogs (Lawrence, 2001). The farrow-to-finish investment returns are not one-month returns; instead, they are returns on investments over a period of time. In addition, the model requires monthly returns for the stocks of the value-added agribusiness firms and the monthly return data for the S&P 500. The daily stock and dividends for the S&P 500 and each of the agribusiness firm stocks along with the return to the one-year U.S. Treasury bill (risk-free rate) are taken from the Center for Research in Security Prices (CRSP, 2002) database. The return to a stock is defined as the change in stock price between consecutive trading days plus any dividends.[4] Because farrow-to-finish return data could be obtained only on a monthly basis, daily rates of return for the stocks were compounded into monthly rates of returns.[5]

The agribusiness firms used in this study are first handlers of pork products beyond the farm gate; thus, they are the next step in the value-added chain. Note that many of these companies have operations beyond the first-handler processing level of the pork products. Companies were selected using NAICS and/or SIC codes corresponding to processors of pork

[4] The daily stock price given by the CRSP database is the closing price or the negative bid/ask average (if a closing price is not available on that trading day). If the company trades on more than one exchange, the last trade is the closing price used. The dividend amount used is the U.S. dollar value per share of distributions resulting from cash dividends, spinoffs, mergers, exchanges, reorganizations, liquidations, and rights issues as defined by the CRSP.

[5] For simplicity when figuring the returns, an investment in the S&P 500 is treated as one of the *i*th agribusiness firms.

Table 1. Companies Used in the Value-Added Portfolios

Company Name	Ticker Designation	Years Invested in as Part of Optimal Constrained Value-Added Portfolio
Bob Evans Farms, Inc.	BOBE	1986, 1996
Bridgeford Foods Corp.	BRID	1987, 1989, 1990
ConAgra, Inc.	CAG	1979
Chiquita Brands Internat., Inc.	CQB	1980, 1985, 1986, 1987, 1990, 2000
Cuisine Solutions, Inc.	CUIS	1991, 1993, 1994
Foodbrands America, Inc.	FDB	1983, 1984, 1985, 1986
Pierre Foods, Inc.	FOOD	1996, 1997
Fleming Companies	FLM	1982, 1987, 1988, 1989, 1990, 1996, 2001
Smithfield Companies, Inc.	HAMS (SFDS)	1982, 1985, 1995, 1996
Hannaford Brothers Co.	HRD	1982, 1984, 1986
Idle Wild Foods, Inc.	IDLE	1981
Piemonte Foods, Inc.	PIFI	1996
Ralston Purina Co.	RAL	1985, 1986
Rica Foods	RCF	1998, 1999
Reymer Foods, Inc.	RYR	1986
Standard & Poor's	S&P 500	1996
7 Eleven Corp.	SE	1996
Seaboard	SEB	1986
Sara Lee Corp.	SLE	1982, 1985, 1996
Thorn Apple Valley, Inc.	TAVI	1992
United Heritage Corp.	UHCP	1992

products.[6] Each company is American based and publicly traded on one of the following exchanges: New York Stock Exchange, NASDAQ, American Stock Exchange, and Over the Counter.

To be eligible for inclusion in an annual portfolio, a stock must have return data for the 60 months prior to January 1 of the annual portfolio being analyzed. For example, the portfolio as of January 1, 2001, had 25 value-added companies that were part of the universe of investments.

[6] The agricultural business firms used in the development of the portfolios belonged to the following NAICS and/or SIC classes as defined by the U.S. Department of Commerce, Economics, and Statistics Administration Bureau of the Census: Industry 2011, Meat Packing Plants; Industry 2013, Sausages and Other Prepared Meats; 2077 Animal and Marine Fats and Oils; 311611 Animal (except Poultry) Slaughtering; 311612 Meat Processed from Carcasses; and 311613 Rendering and Meat By-product Processing.

The historical data for this specific portfolio utilize monthly returns from January 1996 through December 2000. Thus, any value-added company not having monthly return data for the aforementioned dates was excluded from the choice set of stocks used in the development of the portfolio for January 1, 2001. The process is identical for all years prior to 2001. Table 1 provides a list of those companies, their ticker designation, and the year they were selected for inclusion in one of the optimal constrained value-added portfolios.

Testing the Correlation of the Returns

Portfolio theory in finance works on the premise that the input-output relationship between financial assets is linear, implying constant returns to scale (Robison and

Barry, 1987). With perfect negative correlation between the returns to a stock and the returns to the farrow-to-finish operation, the producer faces a situation where he/she can reduce portfolio risk to zero. It is most often the case that there will be imperfect correlation between the asset returns; however, imperfect correlation still allows for diversification. The presence of less-than-perfect positive correlation in asset returns indicates that a portfolio's standard deviation will always be less than the weighted average of the component-asset standard deviations. Thus, the goal of a portfolio is to include assets that exhibit complementarities; i.e., when the return to the *i*th asset is low, then the return to the *j*th asset is stabilizing the returns to the portfolio until all nonsystematic risk is eliminated (Robison and Barry, 1987; Elton et al., 2003).

The second step in the empirical methods was to test the correlation of the investment returns for evidence of the possibility of risk diversification. Table 2 is a correlation table for the universe of value-added stocks in 1990.[7] At least 10 of the 21 value-added stocks exhibit negative correlation with the farrow-to-finish operation for all annual portfolios from 1979–2001. This negative correlation implies diversification of risk is possible; however, it is also possible to receive benefits of diversification even when assets are positively correlated. In essence, the farmer has the ability to eliminate the risk that is unique to the farrow-to-finish operation (nonsystematic risk) with the inclusion of the value-added stocks to the portfolio.

Forecasting Returns Using ARMA and ARIMA Models

Once historical returns were calculated and evidence of correlation was determined, we next needed to identify the correct time-series model for forecasting the future monthly return of each investment opportunity used in the simulation model. The first step was to conduct a Dickey-Fuller unit root test to test for the presence of autocorrelation. The test revealed that the return data for the farrow-to-finish operation were nonstationary; however, the stock returns were stationary. To correct for the problem of nonstationarity, the returns for the farrow-to-finish operation were first-differenced. These transformed data were then retested to determine if they were stationary. Based on the results of the Dickey-Fuller unit root test, the first-differenced data were stationary.

Second, a test was conducted to check for the presence of autoregressive conditional heteroskedasticity (ARCH) which is often present in financial time-series data (Whistler et al., 2004). The presence of ARCH suggests that the variance of the forecast errors depends on the size of the previous disturbance (Greene, 2003). According to the results of the ARCH test on the first-differenced farrow-to-finish returns and the returns to the stocks, the data do not exhibit ARCH.

Next, the type of autoregressive pattern present in the data had to be identified. The ARIMA command in *SHAZAM* creates estimates of univariate ARIMA models. For the farrow-to-finish operation, we use the first-differenced form of the returns data, and the actual returns for the stock data. The identification form of the ARIMA command in *SHAZAM* tests for the appropriate number of autoregressive (AR) and moving-average (MA) terms to use in the estimation and forecasting model with the autocorrelation function (ACF), the partial autocorrelation function (PACF), and the Ljung-Box test.

In addition, *SHAZAM* tests multiple specifications of the autoregressive term and the moving-average term, and plots the ACF and the PACF which aides in the selection of the appropriate AR and MA terms for the estimation and the forecasting model. The plots of the ACF and PACF for both the farrow-to-finish

[7] Additional correlation tables are available from the authors upon request.

enterprise and the stock investments exhibit a spike in the first lag and then follow a declining pattern, which are the characteristics of an AR(1) and MA(1) process (Greene, 2003). Greene also notes that an ARMA (1, 1) process is a workhorse of the applied literature and adequately describes the movement of a given economic time series.

Based on the results of these tests, the one-month forecast and the error terms used in the simulation model should be obtained from an ARMA (1, 1) model for the stock investments and an ARIMA (1, 1) model for the farrow-to-finish operation. The ARMA (1, 1) estimation equation for the returns to the stocks is given by:

$$(1) \quad y_t = \alpha + \phi y_{t-1} - \theta e_{t-1} - e_t,$$

where y_t is the return to a firm in month t, α is the intercept, y_{t-1} is the return from the previous month, ϕ is the coefficient on the autoregressive term, θ is the coefficient on the moving-average term, e_{t-1} is the error term from the previous month, and e_t is the error term in the current month.

The estimation equation for the ARIMA (1, 1) is:

$$(2) \quad y_t = \alpha + \phi(y_{t-1} - y_{t-2}) - \theta e_{t-1} - e_t,$$

where ϕ, the coefficient for the AR term, is now multiplied by the first-differenced returns. The first-differenced farrow-to-finish returns and the actual stock returns are percentage returns.

Next in the process, we take the estimated coefficients along with the error terms from the above equations and generate a one-period forecast of the future returns to the stocks and a one-period forecast of the differenced returns to the farrow-to-finish operation. The resulting forecasts, in combination with the estimated coefficients and the residuals (error terms) from the estimation stage, are the inputs for the stochastic simulation model.

Stochastic Simulation of Returns

The next step in the methods process is to stochastically simulate annual returns for the value-added stocks and the farrow-to-finish operation. The one-month forecasted values generated by the ARMA (1, 1) and the ARIMA (1, 1) plus a randomly selected error term generate the first month's stochastic return. The ARMA (1, 1) and the ARIMA (1, 1) equations, along with their estimated coefficients, are used to determine the next 11 months of stochastic returns for the stocks and the farrow-to-finish operation. Once 12 months of stochastic monthly returns have been generated, they are annualized to create one potential state of nature. The simulation model uses 10,000 iterations, where each iteration of the simulation model generates one annual return. Following is a detailed explanation of the simulation process.

For a single iteration in a simulation, the model begins with a forecasted stochastic return (month 1, or January). At this point, the model chooses one of the historical error terms, all of which are assumed to have an equal probability of occurring. To do this, the stochastic simulation model utilizes the "RISKDUniform Function" available in *@Risk*. The discrete uniform distribution allows the random and independent error term drawn to assume any of the previous 59 months of historical errors. The 60th previous month's error term cannot be used because the first-differencing of the farrow-to-finish returns yields only 59 error terms. In this model, the discrete numbers correspond to a number (1 through 59) associated with one of the previous 59 months of historical error terms for all investments. The simulation grabs the historical error term associated with an observation for month 2 in iteration 1. Whatever observation is selected is then used for all of the stocks and the farrow-to-finish operation for month 2 in iteration 1. This process is repeated a total of 11 times for a single iteration.

Table 2. 1990 Correlation Matrix for the Universe of Value-Added Stocks

	BOBE	BRID	CQB	CAG	SLE	FLM	FSM	GIS	HNZ	HRL	RAL	SFDS	TYSN	SEB
BOBE	1													
BRID	0.165459	1												
CQB	0.128155	0.100606	1											
CAG	0.286540	0.158386	0.273411	1										
SLE	0.279445	0.095831	0.223584	0.845344	1									
FLM	0.554619	0.252702	0.359935	0.358948	0.247887	1								
FSM	0.204144	0.296487	0.198563	0.458282	0.338897	0.425093	1							
GIS	0.101215	0.062007	0.146403	0.181250	0.231346	0.105214	0.309778	1						
HNZ	0.448381	0.200249	0.212748	0.266138	0.268432	0.460756	0.406886	0.249759	1					
HRL	0.252237	0.155898	0.090668	0.028237	0.144816	0.247120	0.140861	0.016654	0.187132	1				
RAL	0.450037	0.068914	0.213878	0.478633	0.433763	0.492812	0.432807	0.254123	0.560012	0.225613	1			
SFDS	0.209006	0.266036	0.256546	0.323156	0.190692	0.376919	0.285412	0.017527	0.213441	0.082547	0.194610	1		
TYSN	0.222734	0.129201	0.142148	0.169944	0.161355	0.365166	0.248092	0.191325	0.347722	0.153275	0.430103	0.140189	1	
SEB	0.166026	0.038821	0.169589	0.183766	0.119732	0.430458	0.371225	0.032340	0.304732	0.206876	0.425235	0.360294	0.251362	1
MO	0.180690	-0.007172	-0.014281	0.128767	0.137768	0.224651	0.319400	0.124030	0.792238	0.139833	0.394654	0.176857	0.427010	0.320956
FDB	0.100759	0.055578	-0.253958	-0.089711	-0.048269	0.010473	0.047802	0.111529	0.118942	0.495583	0.083776	-0.002230	-0.028665	0.004476
CUIS	0.245339	0.108743	0.057546	0.212228	0.112809	0.314576	0.369222	0.269162	0.184531	-0.161821	0.261706	0.209862	0.226878	0.228528
DOBQ	0.245850	0.247113	0.099928	0.186826	0.070621	0.482413	0.345938	0.175392	0.309023	0.175023	0.373173	0.202878	0.179513	0.308979
TAVI	0.138505	0.088457	0.179115	0.092522	0.187305	0.254291	0.115564	0.037268	0.245832	0.152042	0.183639	0.248596	0.334685	0.263596
GH	0.309354	0.035850	0.046916	0.351672	0.237788	0.427606	0.380310	0.199806	0.395575	0.069642	0.625465	0.107953	0.370923	0.308640
HRD	0.406977	0.340959	0.149809	0.367820	0.290767	0.557578	0.537975	0.174108	0.473659	0.175568	0.546944	0.296853	0.181901	0.353678
KAPL	0.092652	0.115380	-0.039870	-0.016675	-0.007081	0.040996	0.038537	0.148428	-0.055433	0.026001	0.141572	-0.049050	-0.054757	-0.277772
RYR	0.361589	0.083134	0.152735	0.167412	0.064041	0.529962	0.364252	0.015890	0.321194	0.288903	0.407196	0.155749	0.147057	0.273499
NAFC	0.405221	0.104883	0.152983	0.165990	0.154003	0.383494	0.306451	0.134758	0.126841	0.547205	0.286051	0.159005	0.240610	0.267589
UHCP	0.016586	0.137484	-0.067442	0.196766	0.218562	0.051535	0.100620	0.105252	0.199212	0.098151	0.209176	0.120898	0.321407	0.019519
FOOD	0.139107	0.354334	0.272675	0.213733	0.076417	0.137402	0.169081	-0.022939	0.057928	0.137037	0.169821	0.227434	-0.109320	0.344041
SandP500	0.520555	0.348200	0.281827	0.485315	0.450522	0.697850	0.593642	0.272795	0.575032	0.331343	0.733810	0.347717	0.425481	0.404637
Farrow	-0.096604	0.032863	0.168116	-0.055345	-0.098910	-0.117790	-0.136456	-0.128269	-0.038983	-0.161125	-0.029212	-0.055450	-0.078979	-0.224790

Table 2. Continued/Extended

	MO	FDB	CUIS	DOBQ	TAVI	GH	HRD	KAPL	RYR	NAFC	UHCP	FOOD	SandP500	Farrow
BOBE														
BRID														
CQB														
CAG														
SLE														
FLM														
FSM														
GIS														
HNZ														
HRL														
RAL														
SFDS														
TYSN														
SEB														
MO	1													
FDB	0.123493	1												
CUIS	0.185705	0.034886	1											
DOBQ	0.240254	0.044768	0.471444	1										
TAVI	0.201044	-0.051384	0.067337	0.162015	1									
GH	0.289380	0.010578	0.339030	0.559049	-0.000931	1								
HRD	0.186682	0.053602	0.385578	0.661732	0.189753	0.520774	1							
KAPL	-0.047158	0.030972	0.109153	0.163922	-0.100390	0.064563	0.079810	1						
RYR	0.212142	0.255010	0.219159	0.528193	0.105427	0.483760	0.548484	-0.052061	1					
NAFC	0.079558	0.103515	0.028745	0.345670	0.206286	0.214922	0.248007	0.203920	0.254701	1				
UHCP	0.187240	0.126251	0.114149	0.082253	0.122669	0.166111	0.102139	0.005292	0.021825	0.072171	1			
FOOD	-0.003276	0.018679	0.093152	0.250075	-0.056444	0.066959	0.174349	-0.090636	0.183399	0.209353	0.055686	1		
SandP500	0.340235	0.057756	0.387262	0.629652	0.275017	0.631290	0.741029	0.031082	0.609784	0.412558	0.289065	0.189732	1	
Farrow	0.075172	-0.163697	-0.036738	-0.070930	0.071412	-0.058898	-0.092318	0.198885	-0.140934	-0.214889	0.013918	-0.055942	-0.097005	1

This approach is known as nonparametric bootstrapping, and it operates under the assumption that for any future month for a given study period, the returns to an investment option are equally likely to have any one of the historical error terms from the data set. In addition, this process maintains the covariance structure present in the historical return data (Winston, 2001). Winston notes another advantage of bootstrapping is that it "creates" the actual shape of the investments' return distribution, i.e., it captures all movements in the market. Specifically, the results of the simulation step of the model provide us with a set of outputs which replicate the entire distribution for the returns to the investments.

Moreover, the distribution of output returns is a function of the input distribution of historical returns that maintains historical correlation among the assets. By capturing the entire distribution of the forecasted asset returns, we assure that when these outputs are used as inputs in the optimization stage of the model we are accurately reflecting the risk in the model. Once the output distribution has been generated, the next step in the methodology is to determine the allocation criteria for the portfolio. The allocation criteria will then be used for the optimization model.

Portfolio Allocation Scenarios

An optimal portfolio is developed for two different constrained investment allocation scenarios. These optimal portfolios are then tested using the actual (ex post) returns from the next subsequent year to determine if the portfolio that included investment in value-added stocks outperformed a portfolio invested solely in the farrow-to-finish operation.

The total investment in each scenario was 100%, but the maximum allowable amount that could be invested in the value-added stocks changed from 0% in the first scenario to a maximum of 21% in the second scenario. The first scenario is sole investment in the farrow-to-finish operation, while the second portfolio scenario allows for investment in both the value-added stocks and the farrow-to-finish operation.

Using data from the 1999 Agricultural Resource Management Survey (ARMS), Mishra, Durst, and El-Osta (2005) found that 7% of an average U.S. farm household's portfolio is comprised of stocks, mutual funds, and other financial assets. Furthermore, the average U.S. nonfarm household maintains 21% of its portfolio in stocks, mutual funds, and other financial assets. Mishra and Morehart (2001) suggest that by adding additional financial assets to their portfolio, farmers could receive benefits in the form of higher expected returns, and reduce the risk associated with farm investments.

Accordingly, the second scenario in our research restricts the portfolio such that it has a maximum of 21% of the portfolio invested in value-added stocks, which is equivalent to what nonfarm U.S. households invest in financial assets but is 14% greater than what U.S. farm households currently invest in financial assets. The second scenario is known as a "style portfolio" in the finance literature and has limits on amounts that can be invested across sectors of the economy (farrow-to-finish operation and value-added stocks), but within each sector the amount invested in each of the individual assets can be varied (Jackson and Staunton, 1999). The style portfolio in this research is designed to create realistic portfolio restrictions for pork producers who want to remain heavily invested in pork production.

The restrictions in the two previous scenarios on the maximum amount of the portfolio that can be invested in value-added stocks may create inefficiencies in a mean-variance framework. For this reason, a third, unconstrained, portfolio was also tested, one in which there was no constraint on the minimum amount to be invested in the farrow-to-finish enterprise.

This portfolio is the optimal risk-efficient portfolio when there are no restrictions on the investments with the exception of no short sales (Jackson and Staunton, 1999; Elton et al., 2003). Finally, the same output distribution is used for each scenario in the optimization portion of the model to ensure the only factor that changes between scenarios is the allocation criteria.

Optimization of the Forecasted Sharpe Ratio

The next step in the methods process was to use the 10,000 stochastically generated returns available for the stocks and the hog operation as inputs in the optimization model for that specific year. The set of correlated stochastic annual returns is used to develop a weighted portfolio that maximizes the forecasted Sharpe ratio [equation (3)]. Maximization of this ratio is accomplished by choosing the mix of investments in a portfolio with the best return per unit of risk, computed over t iterations for each stock for one year.

Mathematically, the calculation for optimizing the forecasted Sharpe ratio is written as:

$$(3)\quad \max_{w_i} S = \frac{\dfrac{\sum_{y=1}^{N} r_{i,y} * w_i}{N} - r_f}{\sqrt{\sum_{y=1}^{N}\left(r_{i,y} * w_i - \left(\dfrac{\sum_{y=1}^{N} r_{i,y} * w_i}{N}\right)\right)}},$$

$$\text{s.t.: } \sum w_i = 1, \text{ where } w_i > 0 \;\forall\, i,$$

and subject to scenario portfolio allocation constraints, where $r_{i,y}$ is the stochastically forecasted annual return to firm i for iteration y, r_f is the risk-free rate of return, and w_i represents the optimal proportion of each investment in the portfolio. It should be noted that w_i is held constant across all N of the iterations. The top half of equation (3) is the expected return to the optimal portfolio minus a risk-free borrowing rate. The bottom half of equation (3) is the standard deviation, the risk, of the optimal portfolio given the weight of each investment in the portfolio (w_i). The model is subject to a nonnegativity constraint on the weights such that the sum of the investment weights for the stocks and the farrow-to-finish operation is equal to 1, preventing short selling or borrowing (DeMiguel and Uppal, 2005).

As suggested by the previous work of Elton and Gruber (2000) and Jacobs, Levy, and Markowitz (2005), not allowing short sales is appropriate, and the reality of short sales is different for each broker and investor. Elton and Gruber note that most investment advisors do not consider short sales as a viable investment alternative when advising their clients on stock and mutual fund investments. In addition, many investments cannot be sold short. Jagannathan and Ma (2003) report that many investors find short sales difficult to implement and therefore exclude them.

Reinforcing the point of Elton and Gruber (2000), Jacobs, Levy, and Markowitz (2005) conclude short sales are not necessary for the individual's portfolio. They contend no single constraint set applies to all long-short investors, so specific constraints must be modeled for each client, and investors cannot sell a security short without limit and then invest the proceeds of the short sale in some other stock. In sum, the authors state the investment broker imposes its own requirements for its own security, and these requirements vary from broker to broker and investor to investor; thus the portfolio analyst must model each client situation differently. Hence, we do not allow short sales in our model.

The model is also subject to three different sets of portfolio allocation constraints depending on the scenario being optimized (value-added constrained, solely farrow-to-finish constrained, and unconstrained). For the value-added constrained portfolio, the portfolio is subject to the following portfolio allocation constraints:

(4) $w_s \geq 0.79$

and

(5) $\sum_{i \neq s} w_i \leq 0.21,$

where s is the investment in the farrow-to-finish operation, and the constraints restrict the minimum and maximum amounts invested in the farrow-to-finish operation and the value-added stocks, respectively.

For the constrained portfolio which can only be invested in the farrow-to-finish operation, the portfolio is subject to the following portfolio allocation constraints:

(6) $w_s = 1$

and

(7) $\sum_{i \neq s} w_i = 0.$

Based on these two constraints, all investment must be in the farrow-to-finish operation and none in the value-added stocks.

Finally, for the unconstrained portfolio, the portfolio is subject to the following portfolio allocation constraint:

(8) $\sum w_i = 1.$

The above constraint places no restrictions on the allocation of investments in the portfolio.

The software used for maximizing the forecasted Sharpe ratio is *Premium Solver Platform V6.5*, a nonlinear genetic algorithm solver add-in for Excel. A nonlinear solver is necessary because the feasible region of the objective is determined by nonlinear constraints.

Ex Post Testing

One goal of this paper was to assess how the optimal style portfolio would perform ex post when compared to investing solely in the farrow-to-finish enterprise. The final step in the methods process was to conduct this ex post testing of the optimal portfolio results. We compute the annual return to the optimal style portfolio from the actual (ex post) monthly returns of the stocks and the farrow-to-finish operation. For example, the optimal style portfolio the pork producer may invest in as of January 1, 2000, is based on the previous 60 months' returns. The formation of this portfolio contains no information about what occurs in the year 2000.

Then, utilizing the actual (ex post) monthly returns from the year 2000, we calculate the annual return to the style portfolio and the annual return to the farrow-to-finish enterprise. The returns are then compared to see if the style portfolio outperformed the returns to the farrow-to-finish operation. This comparison is done to determine if value-added portfolios need to be actively managed—i.e., are annual readjustments and rebalancing sufficient to capture the benefits of a value-added investment portfolio over a portfolio solely invested in a farrow-to-finish operation?

Results

The results are presented in two subsections below: ex ante results and ex post results. Each subsection allows for a direct comparison between the value-added portfolio and the farrow-to-finish-only portfolio. The ex ante results are the before-the-event information a farrow-to-finish operator would have available to consider prior to the start of an investment year. The ex ante results compare the forecasted value-added portfolio to the forecasted farrow-to-finish-only portfolio. The ex ante results will allow for direct comparison between the results in this study and those of prior studies. This comparison is vital because it allows us to examine the impacts of maintaining a static investment set (prior research) versus a dynamic investment set (the current research).

The ex post results are the actual returns the producer would have earned if he or she had used the optimal forecasted

investment strategy; i.e., the ex post results are the forecasted optimal portfolio strategy applied with the actual (ex post) returns. This allows for a direct comparison between the actual (ex post) returns for the optimal forecast value-added portfolio strategy and the actual (ex post) returns for the farrow-to-finish-only portfolio. Furthermore, ex post portfolio analysis has not been conducted in previous research and should provide insight into whether active management of the value-added portfolio is needed.

Ex Ante Results

Constrained Portfolio Results

Over the entire portfolio study period of 1979–2001, results indicate a farrow-to-finish operator's forecasted optimal portfolio that contained publicly held value-added agribusinesses and agri-food companies as part of its overall investments outperformed a portfolio solely invested in the forecasted farrow-to-finish operation. Table 3 provides the summary statistics along with the forecasted Sharpe ratio for all annual portfolios. From Table 3 it can be surmised that over the entire study period the value-added portfolio yields an average forecasted return approximately 7% higher and a standard deviation 3% lower than the forecasted farrow-to-finish portfolio.

As observed from Figure 3, benefits are extracted from these investments in the form of a greater reward per unit of risk taken (indicated by a larger forecasted Sharpe ratio) through vertical diversification. Thus, whenever the producer was given the option of including a value-added company in the portfolio of investments, at least one of these companies was included.

Table 3 also provides a list of the stocks in combination with the proportion of the value-added portfolio allocated to these stocks and the amount invested in the farrow-to-finish operation. For each portfolio, the value-added investment is 21% of the hog producer's style portfolio, the maximum allowable amount. The greatest number of value-added companies in a portfolio was seven in 1986 and 1996, while the value-added portfolio in 1996 was the only portfolio containing investment in the S&P 500. It can be inferred from Table 3 that by allowing the investment universe to change according to available investments, the resulting optimal forecasted portfolio moved in and out of different stocks to maximize the forecasted Sharpe ratio. Previous studies did not incorporate this feature; hence the EV portfolios developed in their models were restricted in their investment choices and constrained the EV frontier to be suboptimal.

Further analysis of the agribusiness companies revealed that the optimal forecasted style portfolio for investment consisted of companies having significant activities beyond the initial processing sector and extending into the wholesale and retail sectors. These results support findings reported by Duval and Featherstone (2002) who conclude pork producers may want to invest in companies whose operations extend into the retailing sector. Thus, the portfolios that included the value-added agribusiness stocks provided the highest risk-adjusted return for each dollar invested; i.e., these portfolios provided the largest reward to risk tradeoff given the risk-free interest rate available for borrowing and lending.

Analysis of the optimal forecasted portfolio using data from various historical data study periods indicates that the advantages of value-added investments have increased over time. The difference between the forecasted Sharpe ratios grew over time, suggesting the reward-to-risk benefit from investment in the value-added stocks has become more valuable. Producers always moved the maximum allowable investment amount out of the hog operation and into value-added stocks. Investments in agribusiness firms that span the vertical channel from processing to retailing tend to be the preferred stocks in the portfolio.

Table 3. Forecasted Portfolio Returns, Farrow-to-Finish (FTF) and Value-Added (VA)

Year	Portfolio Type	% Portfolio in FTF Operation (%)	% Portfolio in VA Companies (%)	Mean Return (%)	Std. Dev. (%)	Risk-Free Rate (%)	Sharpe Ratio	Companies Invested in as Part of the Value-Added Portfolio
1979	FTF	100.00	0.00	-6.80	31.62	5.56	-0.39	CAG
	VA	79.00	21.00	2.75	29.36	5.56	-0.10	
1980	FTF	100.00	0.00	-1.61	24.31	6.18	-0.32	CQB
	VA	79.00	21.00	3.94	23.72	6.18	-0.09	
1981	FTF	100.00	0.00	-4.17	18.75	7.18	-0.61	IDLE
	VA	79.00	21.00	2.10	19.66	7.18	-0.26	
1982	FTF	100.00	0.00	32.21	18.88	8.16	1.27	FSM, SFDS, HRD
	VA	79.00	21.00	31.82	15.36	8.16	1.54	
1983	FTF	100.00	0.00	-10.55	20.34	8.74	-0.95	FDB
	VA	79.00	21.00	5.47	37.64	8.74	-0.09	
1984	FTF	100.00	0.00	7.79	18.97	9.07	-0.07	FDB, HRD
	VA	79.00	21.00	14.74	16.88	9.07	0.34	
1985	FTF	100.00	0.00	9.28	17.42	8.93	0.02	CQB, RAL, SFDS, FDB
	VA	79.00	21.00	14.78	14.40	8.93	0.41	
1986	FTF	100.00	0.00	30.92	18.36	8.26	1.23	BOBE, CQB, RAL, SEB,
	VA	79.00	21.00	31.90	15.09	8.26	1.57	FDB, HRD, RYR
1987	FTF	100.00	0.00	9.28	13.73	6.65	0.19	BRID, CQB, FSM
	VA	79.00	21.00	16.86	12.27	6.65	0.83	
1988	FTF	100.00	0.00	-7.48	19.60	6.44	-0.71	FSM
	VA	79.00	21.00	2.91	16.29	6.44	-0.22	
1989	FTF	100.00	0.00	18.90	19.50	6.11	0.66	BRID, FSM
	VA	79.00	21.00	23.23	15.94	6.11	1.07	
1990	FTF	100.00	0.00	23.38	20.57	6.78	0.76	BRID, CQB, FSM
	VA	79.00	21.00	23.53	17.48	6.78	0.96	
1991	FTF	100.00	0.00	-11.31	19.44	6.65	-0.92	CUIS
	VA	79.00	21.00	-5.39	31.46	6.65	-0.38	
1992	FTF	100.00	0.00	3.45	16.90	6.44	-0.18	TAVI, UHCP
	VA	79.00	21.00	11.95	20.83	6.44	0.26	
1993	FTF	100.00	0.00	-6.77	17.03	6.11	-0.76	CUIS
	VA	79.00	21.00	4.03	31.85	6.11	-0.07	
1994	FTF	100.00	0.00	25.62	16.15	5.65	-1.94	CUIS
	VA	79.00	21.00	-12.42	28.14	5.65	-0.64	
1995	FTF	100.00	0.00	4.07	16.02	5.38	0.59	HAMS
	VA	79.00	21.00	4.00	15.08	5.38	-0.09	
1996	FTF	100.00	0.00	18.39	5.56	5.17	2.38	BOBE, FSM, SFDS, PIFI,
	VA	79.00	21.00	19.60	5.11	5.17	2.82	SE, FOOD, S&P 500
1997	FTF	100.00	0.00	1.53	13.52	5.22	-0.27	FOOD
	VA	79.00	21.00	11.23	21.40	5.22	0.28	
1998	FTF	100.00	0.00	-37.62	12.89	5.38	-3.33	RCF
	VA	79.00	21.00	-29.58	35.36	5.38	-0.99	
1999	FTF	100.00	0.00	-1.62	11.74	5.50	-0.61	RCF
	VA	79.00	21.00	5.11	32.87	5.50	-0.01	
2000	FTF	100.00	0.00	-0.11	11.03	5.51	-0.51	CQB
	VA	79.00	21.00	6.45	21.19	5.51	0.04	
2001	FTF	100.00	0.00	-1.47	3.46	5.49	-2.01	FSM
	VA	79.00	21.00	3.66	10.57	5.49	-0.17	
Average	FTF	100.00	0.00	1.52	16.77	6.55	-0.33	
(1979–2001)	VA	79.00	21.00	8.38	21.22	6.55	0.31	
Std. Dev.	FTF	0.00	0.00	16.35	5.80	1.26	1.18	
(1979–2001)	VA	0.00	0.00	13.68	8.63	1.26	0.84	

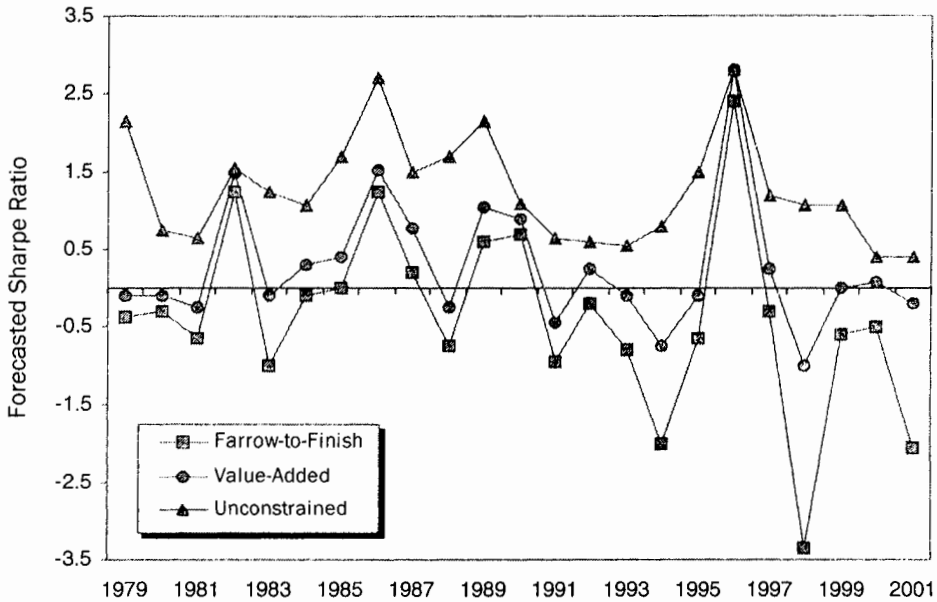

Figure 3. Comparison of Ex Ante Forecasted Sharpe Ratios

These results may be attributable to the changing structure of the agri-food industry, specifically the continuing trend of more value-added activities occurring beyond the production level. Our findings show that markets are increasingly rewarding value-added activities over commodity production (for example, hog production) activities.

Unconstrained Portfolio Results

The restriction on investments for the value-added portfolio was selected in an attempt to design realistic portfolio restrictions for pork producers who want to remain heavily in pork production. However, the restriction of no more than 21% of the portfolio in value-added stocks may create inefficiencies if the optimal unconstrained portfolio contained more than 21% of its investments in value-added stocks. To check for these inefficiencies, a third (unconstrained) portfolio was also tested, one in which there was no constraint on the minimum amount that had to be invested in the farrow-to-finish enterprise.

Figure 3 provides a graphical illustration of the resulting forecasted Sharpe ratios for all three portfolios. As expected, the unconstrained portfolio is found to provide higher Sharpe ratios than the two constrained portfolios, thereby providing the greatest return per unit of risk for a hog producer. However, results also indicate that the optimal unconstrained portfolio for 66% of the annual portfolios examined in this study had no investment in the farrow-to-finish enterprise. In only two of the years for the unconstrained portfolio was a majority of the investment in the farrow-to-finish operation, i.e., greater than 50% of the portfolio. Even for these two years, the amount invested in the value-added stocks is greater than the 21% the average nonfarm household invests in stocks, mutual funds, and other financial assets, and is over three times the amount a farm household invests in these assets (Mishra, Durst, and El-Osta, 2005).

The unconstrained results imply that pork producers may want to consider reinvesting in vertical channels rather than investing in expanded operations.

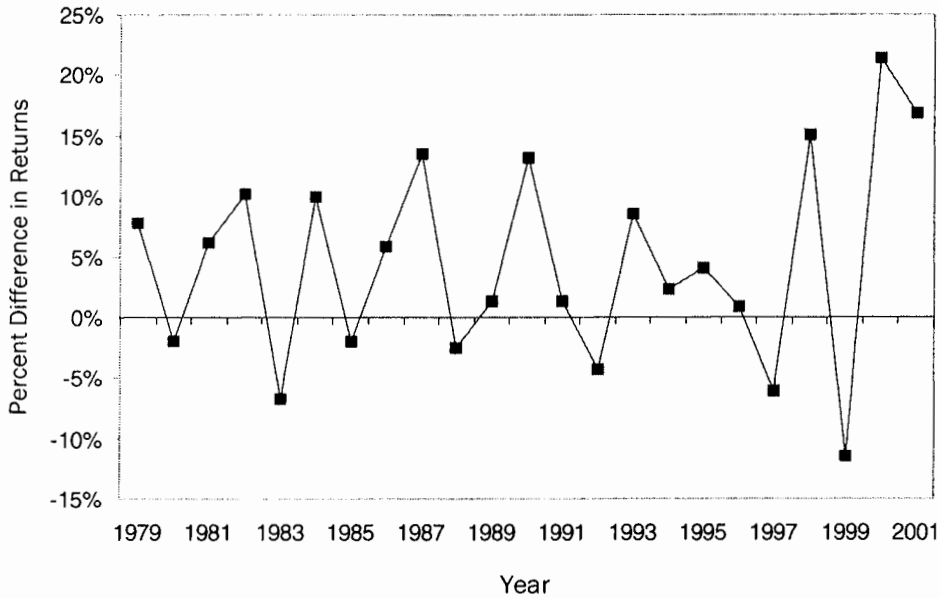

Figure 4. Ex Post Differences in Portfolio Returns: Farrow-to-Finish Portfolio Returns minus Value-Added Portfolio Returns

However, for producers wishing to continue in pork production as their primary business activity, the constrained portfolio results appear more appropriate than the unconstrained results.

Ex Post Results

Perhaps the true test of the benefit of the forecasted optimal style portfolio allocation is how this allocation performed ex post—i.e., does the style portfolio allocation generate a better return than a portfolio containing only the farrow-to-finish operation using the after-the-fact actual returns for both portfolios? For example, how did the forecasted optimal style portfolio for 1979 perform in 1980? It should be noted that the stocks and the weights on these stocks were held constant through the year for which the ex post valuation was conducted. The portfolio was not adjusted during the ex post analysis, and by definition was passively managed. Consequently, the portfolio is unable to account for any additional information the hog producer may acquire throughout the course of the year which would cause him or her to change the combinations of the value-added firms in the portfolio during that single year.

Figure 4 provides a graphical comparison of the difference in the returns between the value-added (style) and farrow-to-finish-only portfolios. In only seven of the 23 years was the style portfolio able to outperform the farrow-to-finish portfolio on a return basis. As illustrated by Figure 4, from 1990 through 2001, the ex post value-added style portfolio only managed to outperform the farrow-to-finish portfolio three times. The worst performance of the ex post style portfolio relative to the farrow-to-finish portfolio occurred in 2000, when the ex post style portfolio's return was approximately 22% less than the farrow-to-finish portfolio. The best performance of the ex post style portfolio relative to the farrow-to-finish operation occurred in 1999, when the ex post style portfolio generated an 11.47% greater return. On average, the farrow-to-finish-only portfolio outperformed the ex post style portfolio by 4.50%.

Prior studies neglected to account for how their optimal portfolios performed on an ex post basis, and as indicated here, on an ex post basis, the value-added portfolio on average underperforms sole investment in the farrow-to-finish operation. This underperformance raises issues regarding how often the value-added portfolio must be rebalanced in order to adjust to any new information that might affect the underlying value of the investments in the returns.

Summary and Conclusions

The results of the analyses in this study reveal that on an ex ante forecasted basis, a hog producer in a farrow-to-finish operation could benefit from investment in value-added stocks. The benefits are an increase in the amount of return per unit of risk for the producer when he/she does not restrict investment solely to the hog enterprise, and benefits derived through diversification and profit capturing in the food channel. Analysis of the optimal portfolio at various historical periods finds that the advantages of value-added investments have increased over time. This result is consistent with a continuing trend of more of the value-added activities in the agri-food industry occurring at the post-production level. The results also consistently show those agribusiness firms that span the vertical channel from processing to retailing tend to be the preferred stocks in the portfolio. Ex ante results are consistent with findings reported by previous research.

The ex post results for the portfolios, however, indicate that the optimal style portfolio does not outperform the sole investment in the farrow-to-finish operation. For 16 of 23 years, the actual returns for a portfolio solely invested in the farrow-to-finish operation were greater than the ex post returns generated by the suggested value-added style portfolio. The differences in the ex ante and ex post results may arise because past performance is not a good predictor of future performance; while the forecasting and simulation models replicate the entire distribution for the returns, maintain the historical correlation among the assets, and accurately reflect the risk of the assets, they may not accurately forecast the returns; market anomalies may occur; and portfolios may require more active management strategies.

The message conveyed by these results is that if pork producers choose to use the stock market as an investment vehicle for managing annual returns, they must choose to actively manage their portfolio or hire someone to actively manage the portfolio on their behalf. The value-added portfolios for pork producers must incorporate new information that might affect the correlation, risk, and returns of the assets in their portfolio if the pork producer is to have a portfolio which accurately reflects market conditions.

It is also worth noting that the study period contained two examples of market anomalies: (*a*) the hog prices observed in 1998, and (*b*) the drastic growth period of the overall market in the late 1990s followed by its rapid decline in the latter part of 2001 and 2002. By "market anomalies," we mean the aforementioned events have not been observed before and may not be observed again. However, it should be pointed out that even with such events, the style portfolio contained investment in value-added stocks in the ex ante simulation. The stock market decline of 2001 caused the ex post style portfolio containing investments in both the farrow-to-finish operation and the value-added stocks to underperform sole investment in the farrow-to-finish operation by 32%.

The research reported here furthers the findings of earlier studies reporting that a portfolio of value-added investments can serve as a source of vertical diversification for pork producers. Moreover, we generate a single optimal portfolio applicable to all risk-averse investors, as opposed to having to discuss all portfolios that lie on the efficient frontier. The results of this study indicate potential for producers to gain

from investing in publicly traded value-added companies, especially those whose operations extend beyond the processing level. In addition, those companies were found to include changes over time—a result not reported in prior research.

Nevertheless, there are some limitations to the study. These include the exclusion of brokerage costs in trading (both economic and financial components), lending constraints for producers, tax costs of changing investments in value-added companies, and the limited number of companies with adequate historical returns data.

A future area of study would be to examine the method chosen for rebalancing the portfolio—i.e., what happens if the portfolios are updated multiple times a year, instead of only changing allocations at the beginning of a year? Evensky (1997) also proposes an additional method he identifies as "contingent rebalancing." With this method, rebalancing is triggered when the equity allocations move away from the original allocation by a predetermined percentage or measure. The actual predetermined target is debatable, and may vary with the type of farm enterprise being examined and the goals of the farmer.

In addition, we recognize that long-term and multi-period investment horizons are important in overall financial planning; these horizons are beyond the scope of the research project reported here. Still, even long-term investment portfolios are generally reevaluated at least once a year (and often more frequently), with allocation changes made (e.g., rebalancing). It is questionable whether unmanaged and unchanged portfolios would remain optimal.

Moreover, the universe of stocks is evolving; i.e., companies may merge with other companies, become private, go bankrupt, new companies may enter the market, etc. These changes certainly occurred during the 28-year data period of this study. Evensky (1997) points out that over time, if portfolios are not revalued, then the portfolio will manifest risk characteristics (as measured by standard deviation) unlike those originally intended, potentially resulting in outcomes significantly different from those projected. This leads to a possible extension of our research for making comparisons of investing for the long-term or short-term gain—i.e., for which method is the wealth at the end of the last period the highest?

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To encourage the publication of peer-reviewed research, Myers Endowment funds will be used to support two awards starting with the Spring 2006 issue of ***Agricultural Finance Review***. The prizes will include a monetary award as well as a certificate. Selected by the editors and on nomination by subscribers to *AFR*, the two awards will be for:

- *Overall Best Journal Article*, and
- *Best Journal Article Authored by a Student.*

All articles are eligible for an award, including invited papers and papers submitted for special issues. There are no specific criteria for determining what constitutes a "best" journal article except that it will be known to be best once read. The student award must have the student as senior author, must have been written principally by the student, and must contain thesis, dissertation, or any other research originated by the student either independently or under the advisement of a faculty. The two awards are mutually exclusive, meaning that if the student award is also the best journal article, only the best journal article award will be given. The winners of the award will be announced annually in the Spring issue of ***Agricultural Finance Review.***

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