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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.

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Credit Risk Migration and Downgrades Experienced by Agricultural Lenders

Brent A. Gloy, Eddy L. LaDue, and Michael A. Gunderson

Abstract

Agricultural credit risk migration is examined using loan records gathered from four agricultural lenders. Results indicate that lender risk ratings are much more stable than ratings based on credit scores estimated from financial statements, highlighting the importance played by nonfinancial factors such as management capacity, character, and collateral in assessing credit risk. Additionally, the borrower's risk tier, personal characteristics, and the stage of the business life cycle provide useful information in predicting credit quality downgrades, while the primary agricultural enterprise does not impact the likelihood of a downgrade.

Key words: agricultural lending, credit quality, credit risk, credit risk migration

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Predicting changes in portfolio credit risk is often based on the credit risk migration of individual loans. The topic of credit risk migration has received a great deal of academic study. Numerous studies have examined how credit ratings assigned to publicly traded bonds by ratings agencies such as Moody's and Standard & Poor's transition over time (Lando and Skodeberg, 2002; Bangia et al., 2002; Crouhy, Galai, and Mark, 2000; Nickell, Perraudin, and Varotto, 2000; Fons, 2002; Carey and Hrycay, 2001). With respect to agricultural lending, the proprietary nature of loan data, small portfolios, and the tendency for lenders to change their rating systems have limited the number of studies that report transitions of loan quality ratings.

Studies of agricultural credit risk migration often have been based on credit scores estimated from farm business financial records. Because lenders consider both financial and nonfinancial factors as well as a borrower's future business prospects, there is good reason to believe that lender credit risk ratings will differ from ratings based on estimated credit scores. The lack of connection between actual practice and previous academic studies makes it important to examine the issue of credit risk migration using actual lender risk ratings. The results will help explain how credit risk transitions over time as well as identify factors which might contribute to changes in credit risk.

The purpose of this study is to examine the extent and causes of agricultural credit risk migration in the portfolios of four agricultural lenders operating in the northeastern United States. The study is

one of the first to use internal lender credit ratings to examine the credit risk migration of agricultural loans. The data include the lender's internal credit rating for each borrower at four annual points in time. This approach overcomes one of the main obstacles to the study of credit risk migration—the proprietary nature of borrower data.

Although the data come from institutions in the northeastern United States, they are regulated by national regulatory agencies, and there is little reason to believe the risk rating processes and standards employed by these institutions are fundamentally inconsistent with risk rating systems and processes used by lenders in other regions. The time, cost, and confidentiality of the data collected also limited the number of lenders from whom such data could be collected. In order to overcome sample size issues, data on a large number of borrowers from these lenders were gathered.

Previous Research

Barry, Escalante, and Ellinger (2002) used farm record keeping association data to examine credit risk migration. Using financial performance data from a large number of Illinois farms over the period 1985–1998, they calculated credit scores for the farms and developed migration matrices describing how the scores changed over time. While this approach is reasonable, it is not clear how closely credit ratings estimated from farm financial performance correspond to the internal credit ratings assigned by agricultural lenders. Many factors make it unlikely that internal credit risk ratings will exhibit as much variability as those estimated from farm financial data.

When originating a loan, the lender decides whether the borrower represents an acceptable credit risk. In this process, the lender balances the costs of loan misclassification associated with type I and type II errors (LaDue, 1989; Nayak and Turvey, 1997). In some cases this judgment may require a great deal of financial information, and in other situations it may require very little. Although most lenders will undertake annual reviews of credit quality, some borrowers may be subject to more frequent and thorough reviews than others. The frequency of review and depth of the analysis may play an important role in the likelihood that the lender's assessment of credit risk will change. While borrowers might experience significant changes in financial performance, unless their situation is reviewed or they experience a payment problem, their credit rating may remain unchanged.

In a study designed to identify important variables for credit risk rating models, Zech and Pederson (2003) conclude it is important to separately consider farm financial performance and repayment capacity. This approach is consistent with the loan officer and the financial institution taking a long-term (multi-year) approach to assessment in which they consider the current economic condition for the type of agricultural enterprise involved. Given the cyclical nature of agricultural prices, periodic "bad years" for any business are almost a certainty. Lenders likely factor these cycles into their original risk rating and any subsequent changes in a borrower's credit risk rating.

Judgment regarding nonfinancial variables also plays a key role in assigning and evaluating credit risk. Among other things, lenders make subjective assessments of the borrower's character, commitment to repay, management capacity, and future business prospects. In a small sample of North Dakota lenders, Gustafson, Beyer, and Saxowsky (1991) found that lenders viewed honesty and integrity as two of the most important subjective borrower characteristics.

The lender's assessment of subjective borrower characteristics such as character plays an important role in the credit risk evaluation process, but their impacts are difficult to quantify (Gustafson, 1989). While financial condition and performance

may change relatively quickly, nonfinancial factors such as character and management capacity are unlikely to undergo sudden or frequent changes. To the extent that nonfinancial factors are important in determining credit ratings, they likely have a stabilizing impact on credit risk ratings. On the other hand, when the lender perceives a change in these factors, credit risk ratings may undergo substantial changes.

Because the loan officer plays a key role in assigning credit risk ratings, these ratings are expected to be more stable than ratings based solely on current and historical financial conditions. Often, the loan officer's judgment plays a central role in determining whether the credit conditions associated with the borrower have changed. In aggregate, these factors raise the possibility that the loan officer will be reluctant to change his or her original assessment, because doing so may signal to superiors that a mistake was made in the original assessment. Also, when a downgrade occurs, the borrower must receive greater monitoring attention, thus requiring more of the loan officer's time and effort.

Although there have been few studies of credit risk migration for agricultural loans, anticipating changes in credit risk is critical to a lender's financial performance. Lenders incur substantial costs when monitoring credit risk. The loan servicing costs associated with high-risk borrowers have been estimated at nearly 100 basis points greater than those associated with low-risk borrowers (Gloy, Gunderson, and LaDue, 2005). If changes in borrowers' credit risk are accurately identified, the lender can reduce costs associated with default. Anticipating credit risk changes also allows the lender to direct scarce monitoring resources to the loans most likely to transition to a higher credit risk category.

Credit Risk Migration

Credit risk migration matrices describe the likelihood that an obligor, bond, or loan in one rating category will remain in that category or transition to another category in a subsequent period. Often, the likelihood of remaining in the same rating category from time t to $t + 1$ is referred to as the retention probability, while the probability of moving to a lower credit quality category is termed a credit downgrade, and moving to a higher credit quality a credit upgrade.

Several studies have been conducted on the credit ratings produced by Moody's and Standard & Poor's. For instance, Fons (2002) notes that for issues in the middle of Moody's ratings scale, the likelihood of upgrading is roughly equal to the likelihood of downgrading, and retention probabilities are often the highest probabilities in credit risk migration matrices. As reported by Nickell, Perraudin, and Varotto (2000), the highest rated credits (on Moody's scale)—Aaa, Aa, and A—exhibit annual retention rates greater than 90%; Baa, Ba, and B exhibit retention rates greater than 80%; and retention rates for credits of quality Caa and lower are less than 70%.

Fewer studies have been conducted on the ratings assigned to borrowers by a financial institution, or internal credit risk ratings. Internal credit risk ratings serve a variety of purposes including guiding loan origination, portfolio monitoring, analysis of adequacy of loan loss reserves, loan pricing analysis, and as inputs to portfolio risk models (Treacy and Carey, 1998).

The lack of analysis of internal credit ratings is not surprising. Carey and Hrycay (2001) point out that few institutions have developed data sets which allow researchers to estimate default and loss experience for their internal rating systems. To estimate default by internal credit rating category, Carey and Hrycay suggest financial institutions often map their ratings into external ratings systems such as Moody's or Standard & Poor's, or rely on credit scoring models to estimate the likelihood of default. The mapping approach is likely problematic in agricultural lending

because in addition to obvious industry differences, agricultural businesses and loans are typically much smaller than those followed by the rating agencies.

Barry, Escalante, and Ellinger (2002) use a slightly different approach and estimate credit scores and credit risk migration matrices from farm business summary data. Their findings indicate retention rates are the highest rates in the credit risk migration matrices, but these retention rates are much lower than those estimated in studies utilizing rating agency data. Their results could be due to the characteristics of the financial performance of agricultural businesses and/or the different types of data used to estimate the matrices. As opposed to the "through-the-cycle" approach used by the rating agencies, the approach of Barry, Escalante, and Ellinger is based on the current and historical financial situation of the farm business.

The financial performance variability found in Barry, Escalante, and Ellinger's study is generally consistent with other studies of farm financial performance. For instance, Gloy, Hyde, and LaDue (2002) found evidence that profitability differences among farms tend to persist—i.e., the most profitable farms in any given year are likely to be the most profitable farms in subsequent years, and the least profitable farms tend to be the least profitable in subsequent years. To the extent that profitability plays a role in credit ratings, this result would lead to conclusions similar to those reported by Barry, Escalante, and Ellinger. Specifically, one would expect to find a tendency for credit ratings to remain constant over time, particularly for the highest and lowest credit ratings.

Data

Historical internal credit risk ratings and additional borrower-level data were gathered from four agricultural lenders. The lenders represent both commercial banks and Farm Credit System associations in the northeastern United States. The lenders all have substantial agricultural loan portfolios, each with an agricultural loan portfolio approaching or exceeding $100 million.

In 2001, loan records for 589 borrowers were examined as part of the credit risk component of a larger research project (LaDue, Gloy, and Cuykendall, 2005; Gloy, Gunderson, and LaDue, 2005). Because most lenders' portfolios contain a large number of small, low-risk relationships, a stratified sampling approach was used in order to obtain adequate data on larger and riskier lending relationships. Each lender's portfolio was stratified by three size and three risk categories. Then, a random sample of borrowers was selected from within each stratum (Table 1). Relationships, not individual loans, were sampled. A loan relationship was defined to include all the loans and people associated with a single business.

The risk categories ranged from borrowers who represented the lowest credit risks to borrowers in the highest credit risk categories. Those in the high-risk category were defined as borrowers whose debts were no longer accruing interest or those for which the lender had taken a write-off of principal and interest obligations. Borrowers in the highest risk category were at least 90 days past due on their interest and principal obligations for at least one loan, and many had experienced loan write-offs within the past year.

The majority of the data were collected from lender computer and paper loan files. Specifically, loan files were examined in order to identify the lender's current credit rating for each borrower and the credit rating assigned to the borrower in 2001, 2000, 1999, and 1998. In some cases the loan files did not contain credit ratings for previous years. For example, the customer may have been recently added to the loan portfolio, and consequently, historical credit risk information was not available. The loan files were also used to gather data regarding loan balances, types and

Table 1. Loan Relationships Sampled, by Size and Risk Class

	Outstanding Relationship Balance, by Size			
Risk Class	**Small (< $100k)**	**Medium ($100–$400k)**	**Large (> $400k)**	**Total**
Low	95	98	96	289
Medium	79	80	67	226
Loss	41	24	9	74
Total	215	202	172	589

terms of loan products, and interest paid by the borrower.

Some data necessary for the study were obtained from a questionnaire completed by the loan officer responsible for the lending relationship. The questionnaire was designed to gather information regarding borrowers' personal and business characteristics and the amount of time spent by various personnel with borrowers over the prior 12 months.

Characterizing the Internal Risk Rating Systems

Regulators such as the Board of Governors (BOG) of the Federal Reserve System and the Office of the Comptroller of the Currency (OCC) divide asset quality into three general categories: pass, special mention, and adverse. As regulators, the BOG and the OCC are particularly concerned about the highest risk loans, those classified as adverse. Both regulators place adverse loans into substandard, doubtful, and loss categories. For loans in these categories, the lender expects to take a loss of interest and/or principal, or expects that the costs of securing and collecting their claims will be substantial.

Although the lenders in the sample represent commercial banks and Farm Credit System associations, their internal credit risk rating systems were similar. In order to make comparisons across lenders, it was necessary to translate each lender's internal credit risk rating into a rating system that could be applied to all lenders. A five-tiered risk rating system was developed for this purpose and is fully described in Table 2.

The top three tiers of the risk rating system consist of pass quality loans. While the BOG and the OCC do not characterize the least risky loans beyond the pass categorization, all of the lenders in our sample used several categories to differentiate among pass quality loans, with some using four and others three. Consequently, when the lender had four categories of pass loans, two categories were merged to result in three tiers of pass quality loans. The financial condition of borrowers in the top three tiers is relatively strong, with solid financial conditions and repayment capacity that declines from tier 1 to tier 3. The amount of monitoring also increases as a borrower moves from tier 1 to tier 3.

The special-mention rating category became the fourth tier in the risk rating system. Each of the lenders used a risk rating category to identify loans in the regulatory category of special mention or "other assets especially mentioned" (OAEM). These borrowers require significant monitoring efforts and have significant weaknesses which threaten repayment capacity.

The fifth tier of the system contained all of the borrowers with adversely classified loans. In general, there were very few lending relationships in the adverse risk

Table 2. Description of the Standardized Five-Tiered Risk Rating System

Tier Level	Description
1	▸ Highest quality credits ▸ Strong financial statements with high levels of profitability, liquidity, and repayment capacity ▸ Very low likelihood of loss in the event of adverse industry financial conditions
2	▸ Strong credits ▸ Financial statements with acceptable levels of profitability, liquidity, and repayment capacity ▸ Strong repayment record ▸ Low likelihood of loss in the event of adverse industry financial conditions
3	▸ Average quality credits ▸ Financial statements are strong enough to justify extension of credit ▸ History of timely repayment ▸ Monitored frequently for compliance with covenants ▸ Modest likelihood of default in the event of adverse financial conditions
4	▸ Classified as special mention or "other assets especially mentioned" (OAEM) ▸ Highly leveraged, and the financial statements reveal several weaknesses that threaten repayment ▸ Require substantial attention ▸ Uncorrected weaknesses may seriously threaten repayment capacity ▸ Currently experiencing adverse economic conditions or, if experienced, then repayment could be jeopardized ▸ Collateral securing the loan may be questionable ▸ Although possible, default is not imminent
5	▸ Classified substandard, doubtful, or loss ▸ Inadequate collateral and repayment capacity ▸ Likelihood of loss of interest and principal is high or the lender must go to great lengths to protect their position ▸ All loans for which interest and principal are in excess of 90 days past due or classified as non-accrual ▸ Repayment likely depends upon collateral

Notes: The descriptions of the regulatory classifications (tiers 4 and 5) draw heavily on the descriptions provided in "Rating Credit Risk" of the *Comptroller's Handbook* (Office of the Comptroller of the Currency, 2001, pp. 16–18). The descriptions of tiers 1, 2, and 3 were developed directly from information provided by the participating financial institutions.

categories. Three of the financial institutions used risk rating systems that directly correspond to the three adverse subcategories used by BOG and OCC. One lender used a more refined internal measure for adverse loans (four categories of adverse loans), and one used a less refined internal measure, grouping all adverse loans into one category. Borrowers in tier 5 are past due on their debt payments, and the lender is likely to take a loss on these loans.

Credit Risk Migration Matrices

Migration matrices were developed to describe the proportion of borrowers who arrived in a risk rating class in period t given their risk rating in period $t-k$. The entries of the credit risk migration matrix for year $t-k$ to year t are given by p_{ij}.

$$p_{ij} = \frac{n_{ij}}{N_i}, \tag{1}$$

Table 3. Financial Conditions Faced by New York State Farms, 1998–2001

Financial Condition	1998	1999	2000	2001
Net cash income per farm [a]	$20,484	$24,675	$26,439	$27,428
Debt-to-asset ratio [b]	18%	18%	18%	18%
Total rate of return on assets [b]	1.93%	1.88%	3.02%	6.53%
Farm debt coverage [b]	1.88	2.20	2.26	2.34

[a] *Source:* USDA, Economic Research Service, U.S. and State Farm Income Database.

[b] *Source:* USDA, Economic Research Service, Farm Balance Sheet Database.

where n_{ij} is the number of borrowers transitioning from credit risk category i to j, and N_i is the number of borrowers in credit risk category i in period $t-k$. Under this formulation, the rows of the migration matrix sum to 1, and the entry in a given cell indicates the proportion of borrowers who began the period in tier i and ended in tier j.

When calculating the migration matrix, each of the observations was weighted for consistency with its proportion in the lenders' portfolios. Weighting was necessary because the study design relied upon a stratified (size and risk) sampling approach when selecting borrowers for analysis. The data cover the years 1998 through 2001, allowing for construction of migration matrices that cover a variety of time intervals. At most, each borrower has a credit risk rating for each of the four years from 1998 through 2001. Because some borrowers entered the lender's portfolio after 1998, the number of borrowers covered by a time period increases through time. For example, the number of borrowers with data for the period 1998–1999 is 521, the number for 1999–2000 is 551, and for 2000–2001 is 576.

As measured by the average farm financial conditions in New York State, the average net cash income, rate of return on assets, and debt repayment capacity increased considerably over the 1998–2001 period (Table 3). Although these measures are not perfect indicators of the economic conditions in other states and the state averages aggregate across all types of farms, it appears the time period was generally favorable to farm financial performance.

Results are presented for one-, two-, and three-year migration matrices (Tables 4–6). The one- and two-year migration matrices (Tables 4 and 5) include results from multiple time periods, while the three-year migration matrix is the only matrix that can be estimated from the data. For instance, the three annual migration matrices (1998–1999, 1999–2000, and 2000–2001) are presented in Table 4. The individual probabilities in the table are the likelihood that a borrower in row i transitioned to column j. The row and column totals report the total proportion of borrowers in each row or column in any given year.

Across all time periods and risk classifications, internal credit risk ratings exhibit high retention rates.[1] For example, the retention rate for the lowest risk borrowers ranged from 98.6% to 93.8% in the annual case (Table 4) to 88.9% in the three-year case (Table 6). Of the lowest risk borrowers (tier 1) experiencing a credit downgrade, the vast majority were

[1] The lenders in the study do not necessarily re-rate all of their loans. While the situation of most loans is evaluated each year, it is possible some performing loans remain in their current category simply because their situation is not thoroughly evaluated. It is difficult to accurately estimate the number of relationships falling under this status, but one would expect that it should be relatively small. The lender has an incentive to accurately assess credit risk deterioration and the borrower has an incentive to encourage the lender to accurately assess credit risk improvement.

Table 4. One-Period Credit Risk Migration Matrices

		2001 Risk Rating					
		1	2	3	4	5	Total
		% of Borrowers					
2000 Risk Rating	1	93.8	5.6	0.0	0.6	0.1	32.5
	2	1.3	91.4	3.0	3.9	0.3	40.3
	3	2.1	2.1	88.9	4.1	2.8	12.4
	4	0.0	0.0	1.2	90.0	8.9	7.8
	5	3.8	0.0	0.0	1.5	94.7	7.1
	Total	31.5	39.0	12.3	9.4	7.9	
		2000 Risk Rating					
		1	2	3	4	5	Total
		% of Borrowers					
1999 Risk Rating	1	97.4	2.6	0.0	0.0	0.0	32.0
	2	1.3	94.4	2.1	1.9	0.3	41.7
	3	0.0	3.1	89.9	2.6	4.3	12.2
	4	0.0	0.0	7.6	84.1	8.3	7.5
	5	0.0	0.0	0.6	8.0	91.4	6.7
	Total	31.7	40.6	12.4	7.9	7.4	
		1999 Risk Rating					
		1	2	3	4	5	Total
		% of Borrowers					
1998 Risk Rating	1	98.6	1.4	0.0	0.0	0.0	32.3
	2	0.0	98.0	0.9	1.0	0.2	42.0
	3	0.0	0.0	97.1	2.9	0.0	11.0
	4	0.0	4.1	4.1	90.9	0.9	7.5
	5	0.0	0.4	1.4	1.7	96.5	7.2
	Total	31.9	41.9	11.5	7.7	7.1	

Note: Sample size for 2000–2001 matrix = 576, for 1999–2000 matrix = 551, and for 1998–1999 matrix = 521.

downgraded one credit quality level to tier 2, and a very small proportion transitioned to special mention (tier 4). Nearly 33% of the institutions' borrowers ended the period in tier 1 (Table 4).

Borrowers in the highest risk tier also showed a very strong tendency to remain in the highest risk category (91.4% to 96.5% in the annual migration cases, Table 4). Roughly 7% of the borrowers were placed in this category. It is important to point out that these results represent borrowers, not loan volume. Migration from the highest risk tier was most often to the special-mention category. For example, from 1999–2000, 8% of the borrowers in tier 5 transitioned to tier 4. Interestingly, there was a relatively large migration probability (3.8%) for high-risk borrowers to the lowest risk tier in 2000–2001. While likelihood of an upgrade of this magnitude is quite low, it is perhaps surprising that credit quality would undergo such an extreme transition. Such changes are likely the result of the restructuring of an adverse loan such as bringing on an additional guarantor, thereby completely changing the credit risk of the situation.

Table 5. Two-Period Credit Risk Migration Matrices

		2001 Risk Rating					
		1	2	3	4	5	Total
		% of Borrowers					
1999 Risk Rating	1	90.9	8.2	0.3	0.6	0.1	32.0
	2	2.7	86.2	4.7	5.6	0.9	41.7
	3	2.3	5.4	79.3	5.7	7.3	12.2
	4	0.0	0.0	8.9	76.7	14.4	7.5
	5	4.2	0.0	0.0	8.0	87.8	6.7
	Total	30.7	39.2	12.4	9.5	8.3	
		2000 Risk Rating					
		1	2	3	4	5	Total
		% of Borrowers					
1998 Risk Rating	1	95.8	4.1	0.1	0.0	0.0	32.3
	2	1.4	92.1	2.9	3.0	0.6	42.0
	3	0.0	3.7	86.8	4.1	5.4	11.0
	4	0.0	4.1	12.2	75.3	8.4	7.5
	5	0.0	0.4	2.0	9.7	87.9	7.2
	Total	31.6	40.7	11.9	8.0	7.9	

Note: Sample size for 1999–2001 matrix = 551, and for 1998–2000 matrix = 521.

Table 6. Three-Period Credit Risk Migration Matrix (1998–2001)

		2001 Risk Rating					
		1	2	3	4	5	Total
		% of Borrowers					
1998 Risk Rating	1	88.9	9.9	0.3	0.8	0.0	32.3
	2	2.9	84.7	4.8	6.4	1.3	42.0
	3	2.8	3.7	78.0	5.6	9.9	11.0
	4	0.0	4.1	13.6	71.6	10.7	7.5
	5	4.2	0.0	1.4	10.1	84.3	7.2
	Total	30.6	39.5	11.8	9.7	8.5	

Note: Sample size = 521.

The migration matrices indicate that for tiers 2–4, there is a greater likelihood of downgrading than upgrading. The only substantial exception to this result is the case of tier 4 in the migration matrices starting from 1998. For example, in the 1998–2001 migration matrix (Table 6), the likelihood of an upgrade from tier 4 is 17.7% versus a 10.7% chance of downgrading to tier 5. For tiers 2 and 3, the likelihood of a downgrade is substantially greater than the likelihood of an upgrade regardless of the time period considered.

The matrices also demonstrate that the likelihood of transitioning to the highest risk category increases substantially as credit quality declines. For instance, it is extremely rare for a borrower in tier 1 or 2 to transition to tier 5. The greatest probability of transitioning from tier 1 or

tier 2 to tier 5 is 1.3%, which occurs for tier 2 borrowers in the three-year matrix (Table 6). On the other hand, the likelihood of a special-mention borrower (tier 4) reaching adverse status (tier 5) is typically 8% to 10%.

The general tendency toward credit risk rating retention declines as credit risk increases until a relationship reaches the highest risk category. In the 1999–2001 matrix (Table 5), the retention rate falls from 90.9% in tier 1 to 76.7% in tier 4 until climbing to 87.8% in tier 5. Both this result and the high likelihood of credit risk rating retention are consistent with and are similar in direction to the analyses of rating agency data summarized in Nickell, Perraudin, and Varotto (2000). While the directional effects appear similar, the magnitudes of the retention probabilities in Tables 4–6 are slightly greater.

The results reported in Tables 4–6 indicate a much lower likelihood of changes in credit risk than those estimated by Barry, Escalante, and Ellinger (2002) who found a 75% retention rate for high quality borrowers, falling to 42%, 42%, 28%, and 35% for lower quality credits. There are several potential explanations for these differences.

Lenders form credit risk ratings on the basis of limited historical data and their perspective on how future conditions will impact credit quality. The results in this study incorporate the significant impact that lender judgment has on credit risk assessment. When evaluating credit risk, most lenders consider factors such as the borrower's character, track record with debt repayment, and collateral. These factors are likely to be much less variable than farm business performance. The internal ratings in this study also reflect the impact of the lender's assessment of future financial conditions. In this respect, the estimates in Tables 4–6 are more representative of a "through-the-cycle" approach to credit risk than a "point-in-time" approach.

Table 7. Proportion of Borrowers with Changes in Credit Risk over the Four-Year Study Period (1998–2001)

Risk Rating	% of Portfolio [a,b]	% of Sample [b]
▸ No change in credit risk	83.9	73.3
▸ Experienced change in credit risk	16.1	26.7
▸ Upgraded	4.8	4.4
▸ Upgraded more than one category	1.1	1.2
▸ Downgraded	11.8	23.0
▸ Downgraded more than one category	4.3	12.3

[a] Population estimates are based upon sample of 521 borrowers.
[b] The total of "upgraded" and "downgraded" does not equate to the total experiencing a change in credit risk because a small number of borrowers experienced both an upgrade and a downgrade.

Were a longer time period considered, economic cycles in the farm sector could possibly influence the credit risk migration matrices estimated in Tables 4–6. However, the different cycle timing for various enterprises likely reduces the impact of cycles on the portfolio (except for the case of an industry-wide recession), and the value of historical data beyond two to three years decays rapidly (Novak and LaDue, 1999).

Explaining Credit Downgrades

Table 7 reports the population estimates as well as the proportion of the sample that underwent changes in credit risk over the four-year period of the study. Consistent with the credit risk migration matrices, no change in credit risk was the most common occurrence, and credit quality downgrades were more prevalent than upgrades. The population estimates suggest that over a four-year period the vast majority (83.9%) of the relationships in the portfolio experienced no change in credit risk, 4.8% were upgraded, and 11.8% were downgraded. The data also indicate it is rare for a borrower to be upgraded or downgraded more than one credit quality category.

A logistic regression model was developed to examine the factors that influence the likelihood of a credit quality downgrade over the period 1998–2001.[2]

$$(2)\quad \text{Prob}(downgrade \mid \mathbf{X}) = \frac{\exp(\beta'\mathbf{X})}{1 + \exp(\beta'\mathbf{X})},$$

where the probability of a credit quality downgrade is a function of a matrix of explanatory variables ($\mathbf{X}$), and β is a vector of parameters to be estimated. Because controls for size and risk are included, the model was estimated with unweighted sample data. This approach does not produce estimates of the population model. Estimating the population model would reduce the impact of size and risk. In other words, weighting by relationship will emphasize the small/low risk loans that are more prominent in a lender's portfolio. Instead, the borrower's average daily loan balance was used to control for size, and indicator variables for the borrower's 1998 risk rating were used to control for initial credit risk level.

The model includes indicator variables identifying the lending institution in order to allow for the possibility that some lenders are more likely to downgrade borrowers than other lenders. Additional variables were included to investigate the influence of a variety of borrower characteristics on the likelihood of a credit quality downgrade—i.e., the primary agricultural enterprise, the lending institution that made the loan, the borrower's business stage, and the borrower's personal stage. The expected impact of these variables is described below.

Nickell, Perraudin, and Varotto (2000) found that factors such as the business cycle and industry impact credit risk migration. To control for industry effects, indicator variables were included to identify whether the borrower's primary agricultural enterprise was dairy, annual crops, livestock other than dairy, permanent plantings, green (horticultural), or other (omitted). Because the collateral and cash flow characteristics of the various types of businesses are different, it is expected that borrowers in some industries may be more likely to experience downgrades. Similarly, different agricultural industries are likely to be in different stages of their industry economic cycle.

Two sets of indicator variables were included to describe borrowers' business stage and personal characteristics. As part of the questionnaire completed by loan officers for each lending relationship, they were asked to identify each borrower's business stage as a beginning farmer, a growing business, a stable business, or a disinvesting/declining business. The characteristics of each stage were defined by a detailed set of instructions given to the loan officers. The business stages were generally defined to correspond to those described by Boehlje and Eidman's (1984) farm business life cycle (Table 8). The questionnaire provided an opportunity to distinguish transferring businesses from disinvesting/declining businesses, but these categories were combined for purposes of analysis. All else equal, beginning and growing businesses are expected to have the greatest chance of experiencing adverse financial outcomes and to have the greatest likelihood of a credit risk decline.

Finally, a set of indicator variables was included to describe borrowers' personal characteristics. Loan officers were asked whether the primary borrower was single, married without children, married with young children, married with college-age children, in their "silver years" (actively involved in the management of the business but children are past college age),

[2] Although it is technically possible to estimate a model that explains upgrades as well as downgrades, there were relatively few upgrades experienced in the sample. Experimentation with a simple logit model for upgrades found no statistically significant parameters. This result limited the interpretive power which might be gained by estimating an ordered logit model. Models that would examine downgrade severity or the number of years in a cell were also beyond the scope of the data, as most downgrade/year cells would contain a very limited number of borrowers.

Table 8. Description of the Borrower Business Stages

Business Stage	Description
Beginning Farmer	A business that has been recently established. This would include a person who just started farming on a full- or part-time basis, or who recently switched from a part-time to an approximately full-time farm. A person in this stage is still dealing with the issues and problems of business establishment.
Growth	An operation that is in the expansion or growth phase of the business. Expansion of the business is a part of the plan of the operator(s). They may have expanded within the last few years or are planning to expand within the next few years. They may be operating in a manner to gradually expand their business.
Stable	A business in which the operator has achieved the maximum size that (s)he desires or believes to be achievable. While modest growth or decline in the size of the business may take place over time, it is not the intent of the management to increase (or decrease) the size of the business.
Decline or Disinvestment	A business that is in the process of being transferred, or a business that is declining in either size or aggressiveness of the manager. The manager may be reducing the size by renting less land or custom hiring functions. The business may be stagnating or atrophying. The operator may be "hanging on" until retirement or sale of the farm.

Source: Adapted from Boehlje and Eidman (1984).

or in retirement. For implementation, the categories were aggregated into single, married (with or without children), silver years, or retirement.

The expected impact of the personal stage variables on the likelihood of a credit quality downgrade is unclear. As individuals pass through different life stages, it is anticipated their financial needs, desires, and risk tolerance will change. For instance, borrowers who are married or approaching retirement should typically have greater cash flow needs and less tolerance for risk than a single individual. If this is true, one would expect that single borrowers would be the most likely to experience a downgrade.

The model was estimated using data from borrowers with credit risk ratings that covered the entire four-year period and who began the period with a credit rating better than the adverse category (tier 5). Excluding these borrowers and those with missing data for explanatory variables resulted in 411 observations. The parameter estimates for the model and the associated marginal effects calculated at the means of the explanatory variables are presented in Table 9. Because the model is nonlinear, the marginal effects change as the levels of the variables change.

The model fit is reasonable, but not outstanding if one considers its success in classifying borrowers who did and did not experience a downgrade over the period (Table 10). The model correctly predicted only 37 of the 117 borrowers who experienced a credit quality downgrade over the 1998–2001 four-year period.

The significance of the group of indicator variables for the lending institution indicates the likelihood of a downgrade varied by lender, with lender 2 having a higher probability of downgrading borrowers (Table 9). Because the model controls for borrower size, risk, and industry types, one can conclude that the lender effect is likely due to institutional differences in how credit quality is analyzed and evaluated. Lenders 2 and 3 had the greatest differences in the likelihood of downgrading.

The borrower's initial risk tier is one of the best predictors of whether a borrower will experience a downgrade. Reinforcing the

Table 9. Parameter Estimates for Credit Quality Downgrade Model (N = 411)

Parameter Description	Estimate	Marginal Effect	Wald χ^2 Statistic
Intercept	-1.0341		2.67*
ADB (average daily balance)	1.00E-06	0.0000	6.54**
ADB^2	-9.00E-14	0.0000	2.50
Lender Group:			
Lender 1	-0.0844	-0.0153	0.05
Lender 2	0.8734	0.1585	5.23**
Lender 3	-0.7859	-0.1427	3.27*
Wald χ^2 statistic for likelihood ratio test of lender group:			18.27**
Risk Group:			
Tier 2 risk	0.6918	0.1256	4.28**
Tier 3 risk	1.4202	0.2578	11.27**
Tier 4 risk	-0.4546	-0.0825	1.16
Wald χ^2 statistic for likelihood ratio test of risk group:			22.28**
Business Stage Group:			
Beginning farmer	-0.1482	-0.0269	0.02
Growth business	-0.3214	-0.0583	0.84
Declining business	1.5791	0.2867	22.10**
Wald χ^2 statistic for likelihood ratio test of business stage group:			25.65**
Personal Stage Group:			
Single (unmarried) borrower	0.4725	0.0858	1.14
Silver-year borrower	-0.6605	-0.1199	4.19**
Retirement	-1.8974	-0.3444	6.17**
Wald χ^2 statistic for likelihood ratio test of personal stage group:			11.10**
Industry Group:			
Dairy	-0.9375	-0.1702	3.20*
Annual crops	-0.6296	-0.1143	1.34
Other livestock	-1.4595	-0.2649	4.14**
Permanent plantings	-0.5582	-0.1013	0.73
Green industry	-1.7910	-0.3251	4.73**
Wald χ^2 statistic for likelihood ratio test of industry group:			7.46
Likelihood ratio test statistic for model significance = 88.97**			
χ^2 statistic for Homer-Lemeshow Goodness-of-Fit Test = 9.90			

Note: Single and double asterisks (*) denote statistical significance at the 0.10 and 0.05 levels, respectively.

conclusions drawn from the migration matrices, the likelihood of a downgrade increases rapidly as credit risk increases beyond tier 1. The explanatory variables for risk rating tier indicate, ceteris paribus, borrowers who were in tier 2 in 1998 had a 12.56% greater chance of experiencing a downgrade than did borrowers who were in credit risk tier 1 in 1998, and borrowers in tier 3 were nearly 26% more likely to downgrade than those in tier 1 (Table 9). In contrast to the data in the credit risk migration matrices, this result is a relatively pure risk effect. Borrowers in tier 4 were not more likely to experience a downgrade than those in tier 1 (the omitted group). This result reflects the fact that similar proportions of borrowers in tiers 1 and 4 experienced downgrades. However, those in tier 4 can only downgrade to tier 5, which has additional regulatory implications, while a downgrade from tier 1 to tier 2, or 3 is primarily for the lender's managerial purposes.

Table 10. Actual and Predicted Credit Quality Downgrades, 1998–2001

		Actual		
		No Change	**Downgrade**	**Total**
Predicted	**No Change**	268	80	348
	Downgrade	26	37	63
	Total	294	117	

Note: The probability cut-off value is 0.50.

The personal and business stage indicator variables show some promise in identifying borrowers who are likely to experience downgrades (Table 9). The significance of these variables highlights the importance of the lender's judgment over nonfinancial factors when assigning credit risk. Borrowers who managed businesses in the disinvesting/declining business stage were by far more likely to experience a downgrade.[3] Borrowers in the beginning, growth, or stable (omitted from model) stages all had similar likelihoods of experiencing a downgrade.

As expected, the personal stage variables indicate older borrowers tend to have a lower probability of credit quality downgrades. The size of the marginal effect is quite large, suggesting the effect is similar in magnitude to the risk effect described earlier. It is likely that these borrowers are operating more established businesses and probably take less relative risk than some of their peers with less established businesses.

As a group, the borrower's primary agricultural industry did not have a substantial impact on the likelihood of a credit risk downgrade. This is not to say that some industries are not more or less risky. However, once the risk tier has been established, agricultural enterprise does not appear to contribute to the likelihood of a credit risk downgrade at meaningful levels of statistical significance.

Summary

The credit risk ratings assigned to 589 borrowers were gathered from agricultural lenders covering the four-year period 1998 through 2001. Each lender's credit risk rating system was mapped into a five-tiered risk rating system in order to compare the ratings across lenders. The ratings were used to develop credit risk migration matrices. The matrices demonstrated a strong tendency for borrowers to remain in their current credit risk class. This tendency was substantially greater than found in the credit risk migration matrices estimated from farm record data by Barry, Escalante, and Ellinger (2002).

In most cases, the likelihood of experiencing a credit quality downgrade was greater than the likelihood of a credit quality upgrade. It is apparent that the probability of transitioning to the adverse credit category (tier 5) increases considerably as credit risk increases. The likelihood of transitioning directly from the lowest risk category to the highest risk category was nearly zero. On the other hand, the chances of transitioning from the special-mention category (tier 4) of the risk rating system to the adverse category (tier 5) ranged from 1% to 14%, depending on the time period considered.

[3] Because the lender's opinion was used to identify businesses that are in decline, it is possible this relationship is endogenous with changes in credit quality. However, this effect should be minimized because the questionnaire developed to collect the information about business stage did not use any mention of credit quality to define the various business stages.

In general, the findings of this study suggest lender risk ratings are more stable than ratings based on credit scores estimated from financial statements. The results highlight the importance played by nonfinancial factors in assessing credit risk. When assessing credit risk, the lender must account for factors such as management capacity, commitment to repay, character, and collateral in addition to financial conditions. The lender's judgment of these factors produces credit risk ratings that are much more stable than ratings produced only from variables constructed from financial statements. Because these nonfinancial statement factors play such an important role in stabilizing credit risk, additional work is needed to identify and understand the factors that lenders consider, how these factors contribute to their assessment, and how these factors influence repayment.

Additional data with a longer time horizon are needed to more completely assess migration. One of the most important issues related to credit risk is the development of an understanding of how internal credit risk ratings relate to actual loan losses. In order to make this assessment, additional data and work are needed to estimate economic losses generated by high-risk and default loans.

Logistic regression was used to examine the roles played by several factors in predicting a credit quality downgrade. Initial risk tier was among the most important determinants of the likelihood of experiencing a downgrade. As credit risk increased, the likelihood of a downgrade increased until the borrower reached tier 4.

Factors such as the borrower's personal characteristics and the stage of the business life cycle provided useful information in predicting downgrades. Borrowers who were actively involved with the business but with children past college age, and borrowers who were in the process of retiring, were the least likely to experience a credit risk downgrade. Among the business stages, borrowers with businesses identified as in the decline or disinvestment stage were by far the most likely to experience a credit risk downgrade. Finally, the type of primary agricultural enterprise did not have a meaningful impact on the probability of downgrades.

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Factors Affecting Farm Credit Use

Ani L. Katchova

Abstract

This study analyzes the personal and farm characteristics that influence the use of farm credit, the degree of indebtedness, and debt consolidation for U.S. farms. Whereas previous studies have examined the supply side of agricultural credit using lender-based data, this study considers the demand side of agricultural credit using representative farm-level data from the USDA's 2001 Agricultural Resource Management Study (ARMS). The results show that gross farm income, risk management strategies, and operator's age and risk aversion had significant influences on the likelihood of farm credit use by rural residence, intermediate, and commercial farms.

Key words: credit, debt, debt consolidation, farm indebtedness

According to the U.S. Department of Agriculture's (USDA's) *Agricultural Statistics*, U.S. farm business debt has been rising for the past decade, reaching $193 billion in 2002. Recent years of low interest rates have provided additional incentives for farmers to purchase land and machinery and to refinance and consolidate debt. Farm business debt varies widely among farms of different typologies, with only a third of small farms, less than half of intermediate-sized farms, and more than three-fourths of commercial farms reporting farm debt balances at the end of 2001. While on average only half of all farmers carry debt from year to year, Ryan and Koenig (1999, 2001) found that some indebted farmers have a particularly high concentration of debt and are in a potentially vulnerable financial position. Despite the significance of farm debt and recent trends toward refinancing and consolidation, little is known about the factors influencing farm credit use.

The objective of this study is to determine the farm and personal characteristics that influence the use of farm credit, the amount of farm credit (degree of indebtedness), and the number of loans (degree of loan consolidation) for U.S. farms. Unlike data sets collected by specific lenders, the USDA's 2001 Agricultural Resource Management Study (ARMS) data used in this study assure the representativeness of the results and conclusions for all U.S. farms. Because farms differ considerably based on their farm typology, the analyses are also conducted separately for rural residence farms (limited-resource, retirement, and residential/lifestyle farms), intermediate farms (farms with sales less than $250,000 whose operators report farming as their major occupation), and commercial farms

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(farms with sales greater than $250,000 and nonfamily farms).

The econometric models used here are those suggested by Katchova and Miranda (2004). Probit models are estimated for farm credit use, while truncated regression and truncated Poisson models are estimated for the degree of indebtedness and debt consolidation, respectively. These models examine cross-sectional differences in credit use, degree of indebtedness, and debt consolidation among U.S. farms.

Related Studies

Based on a review of the literature, only one study was found which considered credit use from the farmer's point of view. Examining the effects of farmers' goals and other characteristics on the amount of credit use, Wise and Brannen (1983) report that farmers' goals of staying in business and improving their families' standard of living were the most important reasons for using credit. However, their study included only an analysis of the degree of indebtedness, using limited farm-level data from Georgia about two decades ago.

Most studies have examined agricultural credit using data for lenders or for borrowers of a specific lender. These studies can be classified into two general groups: (*a*) those examining factors that affect agricultural credit use for financial institutions, and (*b*) those examining factors that distinguish successful versus unsuccessful farm loans.

The first group of studies typically used lender data, and several of them applied two-step estimation procedures. Levonian (1996) applied a two-step Heckman model to examine whether or not banks engage in agricultural lending, and their choices regarding the quantity of agricultural loans. The size of the banks' agricultural branches was identified as the single most important factor in determining agricultural loan levels. Dixon, Ahrendsen, and Barry (1995) also applied a Heckman model to estimate lenders' choices regarding loan approvals and interest rates for hypothetical loans, and concluded that interest rates rose with the loan-to-deposit ratio.

Analyzing the effects of commercial bank structure and other characteristics on interest rates using OLS models and on loan quantities using Tobit models, Bard, Barry, and Ellinger (2000) found loan amounts were not significantly affected by bank characteristics, and interest rates were significantly affected by bank characteristics but only sporadically for certain types of loans.

Barry and Pepper (1985) employed an OLS regression to determine that the loan-to-deposit ratio of agricultural banks was mostly affected by the holding company affiliation. Betubiza and Leatham (1995) extended Barry and Pepper's approach by controlling for selection bias using a Tobit model instead of an OLS model, but reported similar results. Ahrendsen, Dixon, and Priyanti (1994) estimated seemingly unrelated regressions for the changes in commercial banks' shares of farm debt and concluded that the relative risk associated with agriculture and the structure and location of the farms contributed to changes in market shares.

Given the comprehensive research conducted on factors affecting agricultural credit supply, the present study seeks to contribute to the literature by considering factors affecting agricultural credit demand.

Agricultural credit assessment models have been used to evaluate loan applications of potential borrowers (screening) and to assess the credit performance of existing borrowers (loan review). Miller and LaDue (1989) used farm size, liquidity, solvency, profitability, capital efficiency, and operating efficiency to develop credit scoring models for dairy farm borrowers. They estimated logit models to discriminate between successful and defaulting borrowers and observed

that larger borrowers were generally classified correctly using financial ratios. Similarly, Gallagher (2001) found credit assessment models predict that financial ratios (such as leverage, liquidity, profitability, and efficiency) significantly influence loan performance.

Since the investigations cited above were done with lender data, they did not consider farmers who never applied for loans or who were rejected by lenders. Moreover, the factors that explain the acceptance or rejection of potential borrowers and the performance of existing borrowers may or may not be the same factors motivating the use of credit by U.S. farms. This study's contribution is its examination of the demand-side analysis of agricultural credit using farm-level data of borrowers and nonborrowers.

Conceptual Framework

Suppose that a farmer borrows funds from a lender with a specified interest rate. A farmer would borrow such funds when the expected rate of return from the project is greater than the cost of the borrowed funds. Because interest rates and profitability are important determinants of credit use, these factors are included in the empirical analysis. According to the risk-balancing hypothesis, farmers maximize their expected utility where an increase in financial leverage would lead to a decrease in financial risk (Collins, 1985).

Stiglitz and Weiss (1981) developed models for analyzing credit use in markets with imperfect information. Lenders are concerned about the interest rates received on loans and the riskiness of the loans. However, interest rates charged on loans may affect the riskiness of the borrowers' pool because of moral hazard and adverse selection problems. Stiglitz and Weiss showed that credit rationing may exist in equilibrium due to informational problems between lenders and borrowers.

As pointed out by Berger and Udell (2002), because of informational problems, the availability of credit to small businesses may be limited, especially during periods of disequilibrium in the financial markets. Small business lending is generally categorized into four main lending technologies: (*a*) financial statement lending where the evaluation of borrowers is based on balance sheet and income statement data, (*b*) asset-based lending where credit decisions are made based on the quality of the available collateral, (*c*) credit scoring lending where credit scoring models and discriminant analysis are used to determine the creditworthiness of borrowers, and (*d*) relationship lending where lenders make decisions taking into account information gathered through personal interactions or the local community. All of these technologies are used in agricultural lending.

When examining the demand side of agricultural credit, the following caveat applies. Credit decisions are inherently joint decisions between a lender and a farmer, and therefore the lender could effectively reject, restrict, or modify the availability of funds to the borrower. The ARMS data do not include information on whether the existing credit lines are based solely on farmers' credit desires or if they were modified by lenders. Therefore, this study examines cross-sectional differences in the current structure of debt regardless of whether or not some farms have been credit-constrained by lenders. To verify the results here are not driven by such credit constraints, the analysis is repeated for only a subgroup of farmers with favorable income and solvency levels. It is assumed such farmers would not be credit-constrained by lenders.

Econometric Models

Several econometric models examine the factors affecting the debt structure of U.S. farms. Three components of the debt structure are considered here: the use of credit, the amount of credit (degree of indebtedness), and the number of loans

(debt consolidation). The econometric models are adopted from Katchova and Miranda (2004). The models for credit use include both farmers who use credit and those who do not use credit, whereas the models for indebtedness and consolidation include only farmers who use credit.

The first model identifies the characteristics of farmers who are more likely to have debt. Farmer i's use of credit ($c = 1$) or lack of credit ($c = 0$) is estimated with a probit model:

$$(1) \qquad P(c_i = 1) = \Phi(\alpha' \mathbf{x}_i),$$

where $\Phi(\cdot)$ is the cumulative density function, $\mathbf{x}_i$ is a vector of farm and personal characteristics, and α is a parameter to be estimated.

For farmers who use credit, two additional models are defined. An econometric model examines the factors affecting the amount of debt used on the farm. In general, large farms tend to have more debt, which introduces a heteroskedasticity problem. This problem is alleviated by normalizing debt by the total farm assets (Levonian, 1996). Therefore, the analysis considers the degree of indebtedness, which is measured by the debt-to-asset ratio reported by farmers. More indebted farms generally have a higher chance of being financially vulnerable. If a farmer carries debt, then the degree of indebtedness, d, is estimated with a truncated regression model:

$$(2) \qquad f(d_i \mid d_i > 0) = \frac{1}{\sigma}\phi\left(\frac{d_i - \beta' \mathbf{z}_i}{\sigma}\right) \Big/ \Phi\left(\frac{\beta' \mathbf{z}_i}{\sigma}\right),$$

where $\phi(\cdot)$ and $\Phi(\cdot)$ are the standard normal probability density and the cumulative density functions, respectively, $\mathbf{z}_i$ is a vector of farm and personal characteristics, and β and σ are parameters to be estimated.

Another model examines the factors affecting the consolidation of farm loans. Generally, Fair Isaac and Company (FICO) credit scores reported by the three major credit bureaus are worse for consumers with balances spread over a larger number of credit accounts. Here, debt consolidation is measured by the number of loans for each farm. For an indebted farm, the number of loans (k_i) can take values of 1, 2, 3, and so on, and is analyzed with a truncated Poisson model:

$$(3) \qquad P(k_i \mid k_i > 0) = \frac{e^{-\mu_i}\mu_i^{k_i}}{k_i!(1 - e^{-\mu_i})}, \quad (k_i = 1, 2, \ldots),$$

where $\mu_i = e^{\gamma' \mathbf{z}_i}$, and γ is a parameter to be estimated. Both the truncated regression model for the degree of indebtedness and the truncated Poisson model for the debt consolidation are truncated with a lower limit of zero because farms that do not carry debt are not included in these models.

Several personal and farm characteristics are hypothesized to influence the credit use, indebtedness, and debt consolidation of U.S. farms. As noted above, profitability (measured by return on assets) and interest rates are important determinants of credit use. Higher profitability is generally expected to have a positive impact on credit use according to the trade-off theory, and negative impact on credit use according to the pecking-order theory (Fama and French, 2002). Higher interest rates are expected to have a negative influence on the use of debt.

Other factors may also affect credit use. For example, various risk management strategies such as marketing and production contracts, diversification, and crop insurance may mitigate financial risk associated with debt use (Harwood et al., 1999). The operator's age (reflecting different life-cycle stages) and operator's risk attitude (reflecting different risk preferences) may also encourage or discourage the use of debt. Finally, farm characteristics associated with farm size and income, farm type, and business organization may influence credit use.

Table 1. Definitions of Variables and Terms

Variables/Terms	Definitions
Credit Use	1 if farmer has loans; 0 otherwise
Debt Amount	Total debt ($)
Degree of Indebtedness	Debt-to-asset ratio
Debt Consolidation	Number of loans
Gross Farm Income	Gross farm income ($)
Off-Farm Income	Total off-farm income ($)
Return on Assets	Rate of return on assets (%)
Government Payments	Total government payments ($)
Acreage	Total acres operated (owned and leased)
Contracts Use	Proportion of production under marketing or production contracts
Diversification	Entropy index of diversification
Crop Insurance Use	1 if producer received crop insurance payments; 0 otherwise
Land Tenure	Ratio of owned to operated land
Crop Farm	1 if crop farm; 0 otherwise
Age	Age of producer (years)
Education	Education of producer (categorical variable scaled from 1 to 5): 1 = less than high school, 2 = high school degree or GED, 3 = some college, 4 = college degree, and 5 = graduate school
Risk Aversion	Risk-aversion index scaled from 0 to 10, where 0 = producer willing to take as much risk as possible, and 10 = producer avoids risk as much as possible
Individual Farm	1 if individual proprietorship; 0 otherwise
Interest Rate	Average interest rate across all loans weighted by the loan balance (%)
Farm Observations	Number of farms in the ARMS sample
Represented Farms	Weighted number of U.S. farms actually represented by the ARMS sample

One of the advantages of these econometric models is that different personal and farm characteristics may affect credit use, the degree of indebtedness, and loan consolidation of farms. For example, the interest rate variable cannot be included in the probit model examining whether or not farms have debt because farms that do not carry debt will not have interest rates reported for them. In contrast, interest rates can be incorporated in the indebtedness and consolidation models since they include only farms with debt.

Data and Descriptive Statistics

The data are from the 2001 Agricultural Resource Management Study (ARMS) conducted by the USDA. Each farm record is associated with a weight indicating the number of other farms it represents. There are 7,699 farm records included in the 2001 ARMS data, representing 2,149,388 farms in the United States. A delete-a-group jackknife approach with a replication method is used to calculate the standard errors in all estimation models (Dubman, 2000).

Table 1 provides a listing of the variables and their definitions. Summary statistics for all farms are reported in Table 2, and Tables 3 and 4 present summary statistics for farms without debt and with debt, respectively. The USDA has developed three farm typology classes: rural residence farms (limited-resource, retirement, and residential/lifestyle farms), intermediate farms (farms with sales less than $250,000 whose operators report

Table 2. Summary Statistics by Farm Typology

Variables	All Farms	Rural Residence Farms	Intermediate Farms	Commercial Farms
Credit Use	0.41	0.35	0.48	0.63
Debt Amount ($)	57,678	25,598	52,003	281,179
Degree of Indebtedness	0.12	0.12	0.10	0.18
Debt Consolidation	0.73	0.52	0.86	1.58
Gross Farm Income ($)	90,055	18,086	73,163	605,105
Off-Farm Income ($)	57,178	73,844	34,764	24,092
Return on Assets (%)	-0.10	-0.11	-0.12	0.00
Government Payments ($)	7,305	1,823	7,765	40,820
Acreage	455	150	559	2,068
Contracts Use	0.08	0.03	0.11	0.29
Diversification	0.01	0.00	0.01	0.02
Crop Insurance Use	0.08	0.03	0.15	0.21
Land Tenure	0.74	0.79	0.70	0.57
Crop Farm	0.35	0.29	0.44	0.45
Age (years)	55	53	58	51
Education	2.57	2.64	2.40	2.74
Risk Aversion	5.62	5.88	5.41	4.64
Individual Farm	0.91	0.96	0.92	0.54
Interest Rate (%)	3.06	2.64	3.47	4.44
Farm Observations	7,699	1,940	2,435	3,324
Represented Farms	2,149,388	1,287,854	659,933	201,600

farming as their major occupation), and commercial farms (farms with sales greater than $250,000 and nonfamily farms). About 60% of U.S. farms are classified as rural residence farms, 31% are intermediate farms, and 9% are commercial farms.

Farm credit use varies across farm typology (Table 2). Specifically, the percentage of farms carrying debt, the average debt balance, and the average number of loans increase when progressing from rural residence to intermediate to commercial farms. While commercial farms have the highest gross farm income, government payments, and acreage, rural residence farms have the highest off-farm income. Because rural residence farms often do not rely on farming as their major source of income, it is important to consider different farm typologies when analyzing farm credit use.

Commercial farms have the highest use of contracts, highest diversification, highest proportion of farms using crop insurance, and lowest land tenure. Rural residence farms tend to be mostly livestock farms and usually are organized as individual farms. The operators of commercial farms are the youngest among all farm typologies and the least risk averse. Compared to their rural residence and commercial farm counterparts, operators of intermediate farms have fewer years of education. Once again, these statistics reveal inherent differences among the three farm classes—thus necessitating separate analyses based on farm typology.

In comparison to farms that do not carry debt, farms carrying debt are larger, have higher gross farm income and government payments, use more risk management strategies, and have younger and less risk-averse operators (Tables 3 and 4). These comparisons for farms with and without debt are further explored with a probit model.

Table 3. Summary Statistics for Farms with No Debt

Variables	All Farms	Rural Residence Farms	Intermediate Farms	Commercial Farms
Credit Use	0.0	0.0	0.0	0.0
Debt Amount ($)	0.0	0.0	0.0	0.0
Degree of Indebtedness	0.0	0.0	0.0	0.0
Debt Consolidation	0.0	0.0	0.0	0.0
Gross Farm Income ($)	49,361	14,592	50,298	438,575
Off-Farm Income ($)	58,825	70,550	39,231	17,461
Return on Assets (%)	-0.14	-0.12	-0.19	-0.07
Government Payments ($)	3,648	1,407	4,614	24,505
Acreage	340	132	448	2,180
Contracts Use	0.05	0.03	0.07	0.20
Diversification	0.00	0.00	0.00	0.02
Crop Insurance Use	0.04	0.02	0.08	0.10
Land Tenure	0.79	0.80	0.78	0.68
Crop Farm	0.32	0.29	0.38	0.39
Age (years)	58	56	64	52
Education	2.50	2.53	2.39	2.62
Risk Aversion	6.07	6.25	5.83	5.12
Individual Farm	0.91	0.96	0.91	0.32
Interest Rate (%)	—	—	—	—
Farm Observations	3,123	1,188	1,082	853
Represented Farms	1,259,060	839,215	345,709	74,135

Table 4. Summary Statistics for Farms with Debt

Variables	All Farms	Rural Residence Farms	Intermediate Farms	Commercial Farms
Credit Use	1.0	1.0	1.0	1.0
Debt Amount ($)	139,243	73,482	109,218	444,717
Degree of Indebtedness	0.28	0.33	0.21	0.28
Debt Consolidation	1.76	1.50	1.81	2.50
Gross Farm Income ($)	147,603	24,621	98,319	701,961
Off-Farm Income ($)	54,850	80,004	29,849	27,950
Return on Assets (%)	-0.05	-0.08	-0.05	0.04
Government Payments ($)	12,477	2,600	11,232	50,309
Acreage	619	183	681	2,003
Contracts Use	0.12	0.03	0.15	0.34
Diversification	0.01	0.00	0.01	0.03
Crop Insurance Use	0.14	0.05	0.22	0.28
Land Tenure	0.67	0.77	0.61	0.50
Crop Farm	0.40	0.30	0.52	0.49
Age (years)	50	48	52	50
Education	2.68	2.83	2.42	2.81
Risk Aversion	4.97	5.16	4.94	4.37
Individual Farm	0.91	0.96	0.92	0.66
Interest Rate (%)	7.39	7.56	7.29	7.02
Farm Observations	4,576	752	1,353	2,471
Represented Farms	890,328	448,639	314,224	127,465

Regression Model Results

The econometric models examining the factors affecting credit use, indebtedness, and loan consolidation are estimated using STATA. A probit model for the use of credit is estimated, with the results reported in Table 5. The goodness of fit for the regressions is relatively low, possibly due to the large cross-section and heterogeneity of farms. Nevertheless, findings indicate a few factors significantly influence credit use, and these factors often differ based on farm typology. The results show that rural residence, intermediate, and commercial farms with higher gross farm income are more likely to have debt. On the other hand, intermediate farms with higher off-farm income are less likely to have farm debt. Although off-farm income is the primary source of income for rural residence farms, off-farm income does not significantly influence the likelihood of farm credit use for rural residence farms.

According to trade-off theory and the risk-balancing hypothesis, more profitable farms would consider financing their projects with debt; however, the empirical results suggest the return on assets does not significantly influence the likelihood of carrying debt. Commercial farms receiving higher government payments are more likely to have debt, perhaps because government payments stabilize income and mitigate financial risk.

Farmers use various strategies such as marketing or production contracts, crop insurance, and diversification to reduce income risk. Therefore, as expected, farms that contract a larger percentage of their production, purchase crop insurance, and have more diversified farm operations are more likely to have debt. It is also possible, however, that lenders request their borrowers to use marketing and production contracts and crop insurance as a condition for receiving credit. Land tenure affects the likelihood of having debt for rural residence farms. If rural residence farmers own a higher proportion of their farmland, they are more likely to carry farm debt, perhaps because debt was used to finance the purchase of farmland.

Consistent with the life-cycle hypothesis that farmers pay off their debt as they age, the results show that older farmers are less likely to have debt for rural residence and intermediate farms. More risk-averse farmers are less likely to have debt. This result is expected because incurring debt imposes financial risk and presents possible repayment difficulties in the case of income shortfall. Finally, individual farms are more likely to have debt as opposed to farms organized as partnerships and incorporated farms. Overall, the findings indicate farm credit use for all farm typologies is significantly influenced by several factors, including gross farm income, operator's age and risk aversion, and the organizational structure of the farm.

Truncated regression models are estimated to determine the factors affecting the degree of indebtedness (Table 6). These models are estimated only for farms reporting debt (farms with no debt are excluded from this analysis). As shown by the results, intermediate and commercial farms with higher gross farm income and rural residence farms with higher off-farm income are more indebted. These findings are consistent with the fact that the major source of income for rural residence farms is off-farm income.

Intermediate farms with higher acreage and higher return on assets have a lower degree of indebtedness. Land tenure has a negative influence on farm indebtedness for intermediate and commercial farms. Older operators have lower debt-to-asset ratios, once again providing support for the life-cycle hypothesis that farmers pay off their debt as they age. Operators of intermediate farms who are more risk averse tend to have a lower degree of indebtedness. Overall, fewer factors affect the degree of indebtedness than those affecting credit use. Operator's age and income are the most important factors affecting the degree of indebtedness across all farm typologies.

Table 5. Results of Probit Models for Credit Use

Variables	All Farms	Rural Residence Farms	Intermediate Farms	Commercial Farms
Gross Farm Income	6.4E-08	7.2E-06**	2.9E-06**	4.0E-08*
	(1.62)	(3.58)	(4.94)	(1.68)
Off-Farm Income	-4.3E-07	-1.3E-07	-2.1E-06**	1.7E-07
	(-0.98)	(-0.33)	(-2.22)	(0.22)
Return on Assets	0.0057	0.0028	0.0049	0.0012
	(0.12)	(0.11)	(0.01)	(0.02)
Government Payments	7.6E-06**	1.0E-05	5.8E-06	2.7E-06**
	(10.91)	(1.50)	(1.51)	(2.62)
Acreage	6.0E-06	1.2E-04	1.1E-05	-3.3E-06
	(0.97)	(1.49)	(0.50)	(-0.89)
Contracts Use	0.4487**	-0.0446	0.1929	0.3859**
	(3.74)	(-0.15)	(1.23)	(2.45)
Diversification	2.4696**	4.6699	0.6689	0.8147
	(2.35)	(1.37)	(0.21)	(0.66)
Crop Insurance Use	0.5923**	0.4767	0.3226**	0.4219**
	(6.87)	(1.62)	(3.10)	(3.36)
Land Tenure	0.0366	0.3834*	-0.0659	-0.3706
	(0.30)	(1.69)	(-0.39)	(-1.12)
Crop Farm	-0.0140	-0.1559	0.1449	-0.2106
	(-0.15)	(-1.06)	(1.23)	(-1.19)
Age	-0.0271**	-0.0339**	-0.0285**	-0.0080
	(-9.04)	(-7.02)	(-8.81)	(-0.88)
Education	0.0474	0.0932	0.0871*	0.1822
	(1.12)	(1.60)	(-1.87)	(1.26)
Risk Aversion	-0.0800**	-0.0888**	-0.0375*	-0.0635*
	(-4.34)	(-3.63)	(-1.72)	(-1.69)
Individual Farm	0.2640**	0.3773*	0.3132**	0.7300**
	(2.02)	(1.70)	(2.64)	(3.30)
Constant	1.1755**	0.8308**	1.4397**	0.1767
	(5.01)	(2.73)	(4.14)	(0.16)
R^2	0.11	0.14	0.17	0.16
Farm Observations	7,699	1,940	2,435	3,324
Represented Farms	2,149,388	1,287,854	659,933	201,600

Notes: Single and double asterisks (*) denote statistical significance at the 0.10 and 0.05 levels, respectively. Values in parentheses are *t*-statistics.

Factors influencing farm debt consolidation are determined using truncated Poisson models (Table 7). Several common trends emerge for the different farm typologies. Farms that have higher gross farm income and use crop insurance tend to finance their farm operations with more loans. Farm profitability does not affect the number of loans. In addition, more risk-averse farmers are not only less likely to use credit (as found in the probit results), but when they do, they have fewer loans.

The remaining factors have different influences on debt consolidation based on farm typology. Rural residence farms organized as individual farms, as opposed to partnerships and incorporated farms, tend to spread their debt over

Table 6. Results of Truncated Regression Models for the Degree of Indebtedness

Variables	All Farms	Rural Residence Farms	Intermediate Farms	Commercial Farms
Gross Farm Income	2.8E-08	1.2E-06	2.3E-06*	1.9E-08**
	(1.24)	(0.85)	(1.83)	(1.99)
Off-Farm Income	1.0E-06	9.0E-07**	2.8E-06	2.3E-07
	(1.51)	(2.07)	(1.31)	(0.32)
Return on Assets	-0.3633**	-0.3562	-0.3736**	0.2432
	(-2.21)	(-0.85)	(-7.54)	(1.49)
Government Payments	1.1E-06	6.7E-06	-1.7E-06	5.3E-07
	(1.52)	(1.17)	(-0.26)	(0.95)
Acreage	-1.0E-05	-3.2E-04	-8.1E-05**	-4.1E-06
	(-0.81)	(-1.25)	(-1.98)	(-0.45)
Contracts Use	0.2991	-0.0705	0.3411	0.2736
	(1.16)	(-0.19)	(1.41)	(1.32)
Diversification	0.0768	0.0836	0.5422	-0.1813
	(0.09)	(0.05)	(0.30)	(-0.16)
Crop Insurance Use	-0.0041	-0.0642	0.0198	0.0656
	(-0.03)	(-0.20)	(0.11)	(0.64)
Land Tenure	-0.0285	0.1271	-0.4245**	-0.5417*
	(-0.13)	(0.67)	(-2.02)	(-1.83)
Crop Farm	-0.2481	-0.1322	-0.1869	-0.4284**
	(-1.45)	(-1.05)	(-0.89)	(-2.35)
Age	-0.0374**	-0.0245**	-0.0304**	-0.0139*
	(-3.03)	(-4.34)	(-2.46)	(-1.77)
Education	0.0930	0.0593	-0.0369	0.0697
	(1.25)	(0.96)	(-0.48)	(1.28)
Risk Aversion	-0.0162	0.0047	-0.0563**	-0.0199
	(-0.60)	(0.18)	(-2.04)	(-0.51)
Individual Farm	-0.0254	0.3156	-0.0462	-0.0672
	(-0.19)	(1.05)	(-0.25)	(-0.59)
Interest Rate	-0.0109	-0.0096	0.0151	-0.0091
	(-0.28)	(-0.23)	(0.37)	(-0.22)
Constant	0.7921**	0.3071	0.7545	0.3171
	(1.99)	(0.55)	(1.40)	(0.56)
Wald χ^2	34.74**	76.09**	160.12**	12.50
Farm Observations	4,576	752	1,353	2,471
Represented Farms	890,328	448,639	314,224	127,465

Notes: Single and double asterisks (*) denote statistical significance at the 0.10 and 0.05 levels, respectively. Values in parentheses are *t*-statistics.

more loans. Commercial farms that are able to obtain lower interest rates tend to have more loans, perhaps because farmers may use vendor financing for various purchases.

Some farmers apply for credit but are rejected by lenders. The Survey of Consumer Finances, for example, inquires whether or not consumers are rejected for credit, but credit-constrained farmers are not identified in the ARMS data. In this study, farmers with a favorable income and level of solvency are assumed not to be credit-constrained by lenders. The USDA's criteria for income and solvency classes are used, where farms with a negative net farm income and a

Table 7. Results of Truncated Poisson Models for Debt Consolidation

Variables	All Farms	Rural Residence Farms	Intermediate Farms	Commercial Farms
Gross Farm Income	1.7E-08**	3.5E-06**	2.3E-06**	1.1E-08**
	(2.91)	(2.57)	(4.50)	(2.56)
Off-Farm Income	-7.1E-07	-6.4E-07	2.8E-06**	-4.2E-08
	(-0.82)	(-0.47)	(2.49)	(-0.09)
Return on Assets	0.1226	0.0166	0.0684	0.0443
	(1.16)	(0.13)	(0.42)	(0.57)
Government Payments	6.2E-07	8.1E-06	3.0E-06	2.5E-07
	(0.93)	(0.89)	(0.85)	(0.84)
Acreage	1.0E-05**	1.4E-04**	6.5E-06	-2.8E-06
	(2.28)	(2.60)	(0.25)	(-0.54)
Contracts Use	0.2537	-0.3765	0.0586	0.0770
	(1.47)	(-1.03)	(0.35)	(0.75)
Diversification	-0.2520	-5.2109*	-2.5067	-1.3419
	(-0.43)	(-1.64)	(-0.91)	(-1.43)
Crop Insurance Use	0.4362**	0.5299**	0.2685**	0.2171**
	(5.54)	(2.63)	(2.75)	(2.52)
Land Tenure	-0.3757**	0.0280	-0.0969	-0.3517*
	(-2.25)	(0.06)	(-0.50)	(-1.74)
Crop Farm	-0.0326	-0.0744	-0.1360	-0.0330
	(-0.39)	(-0.35)	(-0.83)	(-0.29)
Age	-0.0055	-0.0166	-0.0089**	-0.0018
	(-0.93)	(-1.01)	(-2.07)	(-0.28)
Education	0.0344	0.1084**	-0.0299	-0.0146
	(1.07)	(2.42)	(-0.54)	(-0.27)
Risk Aversion	-0.0620**	-0.0906**	-0.0092	-0.0482**
	(-3.23)	(-2.44)	(-0.33)	(-2.76)
Individual Farm	-0.1448	0.8999**	-0.0396	0.0366
	(-1.48)	(2.59)	(-0.21)	(0.51)
Interest Rate	-0.0763**	-0.0251	-0.0458	-0.0886**
	(-3.17)	(-0.52)	(-1.01)	(-4.20)
Constant	1.5140**	-0.0617	0.8899*	1.8307**
	(4.21)	(-0.07)	(1.83)	(7.01)
R^2	0.04	0.07	0.06	0.05
Farm Observations	4,576	752	1,353	2,471
Represented Farms	890,328	448,639	314,224	127,465

Notes: Single and double asterisks (*) denote statistical significance at the 0.10 and 0.05 levels, respectively. Values in parentheses are *t*-statistics.

debt-to-asset ratio greater than 0.4 are classified as financially vulnerable. Moreover, new models were also estimated excluding farms in financially vulnerable positions. Although not presented here, the significance of the results generally remains the same, except the return on assets no longer influences the indebtedness of farms, and the use of contracts is now associated with more loans. The results of these additional models show that credit constraints possibly imposed by lenders do not significantly affect the findings reported here.

Summary and Conclusions

This study examines the farm and personal characteristics affecting the use of credit, the degree of indebtedness, and

loan consolidation for U.S. farms. The econometric models suggested by Katchova and Miranda (2004) are estimated using 2001 ARMS data. The results identify a few common trends among rural residence, intermediate, and commercial farms. Farms with higher gross farm income are more likely to have debt, are more indebted, and have more loans. Older operators are less likely to hold debt and are less indebted, following the life-cycle hypothesis. Operator's risk aversion has a negative influence on the likelihood of using credit and on the number of loans. Farm profitability and interest rates on existing debt generally show little impact on the credit use, indebtedness, and debt consolidation of U.S. farms.

While many previous studies have considered the factors affecting agricultural credit supply based on lender data, this analysis considers the demand side of agricultural credit using farm-level data. Agricultural credit supply studies usually have concluded that financial factors are the most important in predicting acceptance or rejection of potential borrowers and distinguishing between successful and unsuccessful loans. However, findings of this study suggest nonfinancial factors, such as operator's age and risk aversion, farm structure, and the use of risk management strategies, play a significant role in distinguishing borrowers from nonborrowers.

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The Sustainability of Return on Assets Among Sectors in the Food Economy

Michael Boland and Sara Schumacher

Abstract

Using return on assets as a proxy for profitability, this study evaluates the sustainability of profits in the food economy with respect to industry, corporate, and business-specific effects for low- and high-performing firms. The food economy is broken into its four major sectors: food processing, wholesale grocery, retail supermarket, and restaurant. Industry incremental effects are not significantly different between low and high performers except in processing. On average, high performance has been more sustainable than low performance. Corporate and segment sustainability rates were larger for high performers as compared to low performers. Within the retail industry, there is no significant difference between sustainability rates of high and low performers. High performers in the retail industry had significantly greater industry, business-segment, and total-sum sustainability rates than the other three sectors, suggesting the retail sector has important characteristics that merit further research.

Key words: agribusiness, food, profitability

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Innovation often has been viewed as a measure of ensuring that industries evolve in a characteristic pattern. Schumpeter (1942) called this "creative destruction." His argument asserts firms must continue to be innovative to remain profitable relative to their competitors. Previous research has noted that some firms and industries consistently remain profitable over time, however, suggesting profits may erode at different rates in an industry (Mueller, 1977; Rumelt, 1991; Schmalensee, 1985; Waring, 1996; McGahan and Porter, 2003; Schumacher and Boland, 2005).[1]

The literature generally identifies three types of competition. "Classical competition," as defined by Schmalensee (1985), is typically defined as monopolistic or oligopolistic competition (Bain, 1956). This literature suggests that the differences in competitive advantage across firms in a sector are small because firms collude to raise prices and create barriers to entry (Thomas and D'Aveni, 2004). The second type of competition is termed "resource-based" (Barney, 1991; Peteraf, 1993). According to the literature, there are significant differences in competitive advantage across firms in a sector because firms have different types of resources and these create economic rents (Schmalensee, 1985; Rumelt, 1991). Studies focusing on the third form of competition, labeled "hypercompetition"

[1] Political or institutional factors, such as new governmental regulations or changes in public policy, may affect the sustainability of profits. The breakfast cereal industry is an example in which public policy strategy in the mid-1990s was effective in advancing price competition and ultimately reducing return on assets of cereal manufacturers (Cotterill, 1998).

(D'Aveni, 1994; Hamel, 2000), report that firms face constant erosion of competitive advantage but also benefit from the creation of new competitive advantage (Wiggins and Ruefli, forthcoming 2005).

Based on the findings of these earlier studies examining the three types of competition, the ability to sustain profits may be due to industry, corporate, or business-specific factors. The ability to sustain profits is supported by industry and resource-based views. Industry effects contributing to sustainability of profits may include industry structure that provides barriers to entry and impedes new entrants (e.g., Bain, 1956; Caves and Porter, 1977). Industry effects are defined as industry structural characteristics, such as economies of scale, capital intensity, and degree of vertical integration, which impact the performance of individual firms.

As an example, Smithfield Foods is vertically integrated in pork production and processing (Goldberg, Knoop, and Lane, 2000). This vertical integration includes proprietary animal genetics, feed, and other inputs—together yielding a pork carcass with superior quality attributes that are difficult to emulate by competitors. For Smithfield, vertical integration clearly is a positive industry effect, having led to an above-average return on assets for this firm in the pork processing industry.

Corporate effects are defined as characteristics of a firm's profits attributable to its pattern of diversification. For example, Archer Daniels Midland (ADM) has diversified into corn sweetener production, ethanol production, and processing of agricultural commodities. If this diversification lends itself to economies of scale such that it generates greater profits (above the industry average), then ADM's pattern of diversification into related industries would suggest a positive corporate effect.

Finally, business-specific effects are defined as characteristics of a firm such as superior leadership, better organizational design, greater management of inputs such as labor, and other similar factors, which lead to above-average profit in that industry. Welch Foods, a wholly owned subsidiary of the National Grape Cooperative with above-average profits in the fruit-based foods industry, is a case in point. Welch's competitive advantage is due to the firm's sourcing of superior inputs through its cooperative structure, resulting in the majority of Concord and Niagara grapes being processed into juice, ingredient, and other fruit-based products (Amanor-Boadu, Boland, and Barton, forthcoming 2006).

Previous research has looked at businesses aggregated across sectors as well as within sectors. However, based on findings of studies specifically examining the manufacturing and services industries, there are differences between firms having consistent above-average and below-average profits (McGahan and Porter, 2003; Hawawini, Subramanian, and Verdin, 2003).

This study contributes to the literature on high- and low-performing firms by focusing on the food economy. Using return on assets as a proxy for profitability, our objective is to evaluate the sustainability of profits in the food economy with respect to industry, corporate, and business-specific effects for low- and high-performing firms. The food economy is broken into its four major sectors: food processing, wholesale grocery, retail supermarket, and restaurant. By focusing on low- and high-performing firms, we are able to discern how competitive advantage as measured by profitability erodes over time in these sectors.

The sustainability of return on assets is defined here as the tendency to repeat above-average (below-average) performance from one period to the next. We differentiate between high performers and low performers when analyzing sustainability. A high performer (low performer) is defined as a business segment having return on assets above

(below) the median for all segments in the first time period for which we have a complete record on the segment.[2] The ability to sustain return on assets is then measured by the sustainability rates we estimate, as further explained in the next section.

Theoretical Model

Following the framework used by McGahan and Porter (1999) to analyze various manufacturing and service industries, return on assets of a business segment consists of year, industry, corporate, and business-segment effects. A business segment is defined as a portion of a company's operations that are reported under a single four-digit Standard Industrial Classification (SIC) code. In our model, business segment return on assets above or below the average is specified as:

$$(1)\quad r_{i,k,t} = \sum_{t} \gamma_t d_t + \sum_{i,t} \alpha_{i,t} d_{i,t} + \sum_{k,t} \beta_{k,t} d_{k,t} + \phi_{i,k,t},$$

where $r_{i,k,t} = \Pi_{i,k,t} - \mu$; $\Pi_{i,k,t}$ is the ratio of operating income to assets of the business segment in sector i (i = processing, wholesale grocery, retail supermarket, restaurant) for corporation k at time t; μ is the average return on assets over all business segments in all years; γ_t is the increment to return on assets shared by all business segments in year t; d_t is a binary variable equal to 1 if the observation applies to year t, and 0 otherwise; $\alpha_{i,t}$ and $\beta_{k,t}$ are industry and corporate effects, respectively; $d_{i,t}$ is a binary variable equal to 1 if the variable applies to sector i at time t, and 0 otherwise; $d_{k,t}$ is a binary variable equal to 1 if the variable applies to corporation k at time t, and 0 otherwise; and $\phi_{i,k,t}$ is the residual representing the increment to profit that is specific to the segment. If a corporation has only one segment, it is assumed there is no corporate effect.

[2] McGahan and Porter (2003) used this method to distinguish between low and high performers.

We further divide return on assets above or below the average and each of the effects into a fixed effect and an incremental effect, as follows:

$$(2)\quad r_{i,k,t} = f^{r}_{i,k} + g^{r}_{i,k,t},$$

$$(3)\quad \gamma_{i,k,t} = f^{\gamma}_{i,k} + g^{\gamma}_{i,k,t},$$

$$(4)\quad \alpha_{i,k,t} = f^{\alpha}_{i,k} + g^{\alpha}_{i,k,t},$$

$$(5)\quad \beta_{i,k,t} = f^{\beta}_{i,k} + g^{\beta}_{i,k,t},$$

and

$$(6)\quad \phi_{i,k,t} = f^{\phi}_{i,k} + g^{\phi}_{i,k,t},$$

where $f^{\phi}_{i,k}$ is the fixed component of the segment effect, and $g^{\phi}_{i,k}$ is the incremental component of the segment effect. Other variables can be interpreted similarly.

The fixed effects represent sources of return on assets associated with events and conditions before the beginning of our data (described in the next section). The incremental effects represent sources of return on assets (from industry or business-specific) that are established during the period under study.

We use first-order autoregressive models, specified as follows:

$$(7)\quad g^{r}_{i,k,t} = \rho_{i,k} g^{r}_{i,k,t-1} + \varepsilon^{r}_{i,k,t},$$

$$(8)\quad g^{\gamma}_{i,k,t} = \rho_{YR,i,k} g^{\gamma}_{i,k,t-1} + \varepsilon^{\gamma}_{i,k,t},$$

$$(9)\quad g^{\alpha}_{i,k,t} = \rho_{IN,i,k} g^{\alpha}_{i,k,t-1} + \varepsilon^{\alpha}_{i,k,t},$$

$$(10)\quad g^{\beta}_{i,k,t} = \rho_{CP,i,k} g^{\beta}_{i,k,t-1} + \varepsilon^{\beta}_{i,k,t},$$

and

$$(11)\quad g^{\phi}_{i,k,t} = \rho_{BS,i,k} g^{\phi}_{i,k,t-1} + \varepsilon^{\phi}_{i,k,t},$$

where $\rho_{i,k}$, $\rho_{YR,i,k}$, $\rho_{IN,i,k}$, $\rho_{CP,i,k}$, and $\rho_{BS,i,k}$ are the sustainability rates, and the terms $\varepsilon^{r}_{i,k,t}$, $\varepsilon^{\gamma}_{i,k,t}$, $\varepsilon^{\alpha}_{i,k,t}$, $\varepsilon^{\beta}_{i,k,t}$, and $\varepsilon^{\phi}_{i,k,t}$ are random shocks that are normally distributed with zero mean. In each equation, sustainability is the proportion of the incremental effect at time $t-1$ that systematically remains at time t. No restrictions are placed on the fixed or

incremental effects, so either effect can be negative. This general specification allows for the sustainability of an incremental effect to carry over more than one year.

Further derivation of the model requires substitution of lagged values in equations (2)–(6) into equations (7)–(11), and then substitution of the resulting expressions into equations (2)–(6). Further additional derivation of the model requires subtracting the time means of equations (A1)–(A5) in the Appendix from themselves. This results in the following first-order autoregressive models, which are estimated using ordinary least squares (OLS):

$$(12)\quad r_{i,k,t} - r_{i,k,\underline{t}} = \rho_{i,k}(r_{i,k,t-1} - r_{i,k,\underline{t-1}}) + \psi_{i,k,t},$$

$$(13)\quad \gamma_{i,k,t} - \gamma_{i,k,\underline{t}} = \rho_{YR,i,k}(\gamma_{i,k,t-1} - \gamma_{i,k,\underline{t-1}}) + \lambda_{i,k,t},$$

$$(14)\quad \alpha_{i,k,t} - \alpha_{i,k,\underline{t}} = \rho_{IN,i,k}(\alpha_{i,k,t-1} - \alpha_{i,k,\underline{t-1}}) + \nu_{i,k,t},$$

$$(15)\quad \beta_{i,k,t} - \beta_{i,k,\underline{t}} = \rho_{CP,i,k}(\beta_{i,k,t-1} - \beta_{i,k,\underline{t-1}}) + \xi_{i,k,t},$$

and

$$(16)\quad \phi_{i,k,t} - \phi_{i,k,\underline{t}} = \rho_{BS,i,k}(\phi_{i,k,t-1} - \phi_{i,k,\underline{t-1}}) + \kappa_{i,k,t}.$$

The variables γ, α, β, and ϕ with an underlined subscript can be interpreted similarly. The last term in each equation represents the residuals, which are assumed to be normally distributed with a zero mean. The parameters (sustainability rates) to be estimated are $\rho_{i,k}$, $\rho_{YR,i,k}$, $\rho_{IN,i,k}$, $\rho_{CP,i,k}$, and $\rho_{BS,i,k}$, where the subscripts *YR*, *IN*, *CP*, and *BS* denote, respectively, year, industry, corporate, and business segment for the corresponding estimated sustainability rates. Thus, the fixed and incremental effects in equations (2)–(6) can be derived from the sustainability rates estimated in equations (12)–(16).

Estimating Effects

Because equation (1) is overspecified and the year terms $\Sigma_t \gamma_t d_t$ are collinear with industry-year terms, $\Sigma_{i,t} \alpha_{i,t} d_{i,t}$ cannot be estimated by using OLS. Therefore, we calculate the coefficients in equation (1) by dividing return on assets into means by year, industry, and corporate effects—the same method used by McGahan and Porter (1999). To obtain the estimates, we first calculate μ as the average return on assets of all business-segment observations. Second, the year effects (γ_t) are calculated from the averages of the residual return on assets of business segments at time *t* after subtracting μ. Industry effects ($\alpha_{i,t}$) are the averages of the return on assets of business segments at time *t* after subtracting both μ and γ_t. Corporate effects ($\beta_{k,t}$) are obtained from the averages of the return on assets of segments at time *t* after subtracting μ, γ_t, and $\alpha_{i,t}$. The residual ($\phi_{i,k,t}$), which is the remainder after subtracting all of the previously estimated effects (μ, γ_t, $\alpha_{i,t}$, and $\beta_{k,t}$), is interpreted as a segment effect. In summary, means are computed in the order of year, industry, corporate, and business segment.

Data

Data for this study were obtained from the Standard & Poor's Compustat Business-Segment Reports for business segments in the food economy for the 1980 to 2001 time period. This initial data set contains 9,844 business segments (e.g., observations in 57 different four-digit SIC classifications), of which 324 business segments are excluded because each is the only corporation within its SIC classification. To calculate lagged effects, we eliminate the first observation on each business segment, leaving a total of 7,900 business segments. Only those segments with at least six years of data are considered in estimating sustainability rates.

Return on assets of low- and high-performing business segments by sector and year are reported in Figures 1–5. As previously noted, a high performer (low performer) is defined as a business segment that has return on assets above (below) the median in the first time period for which we have a complete record on the segment.

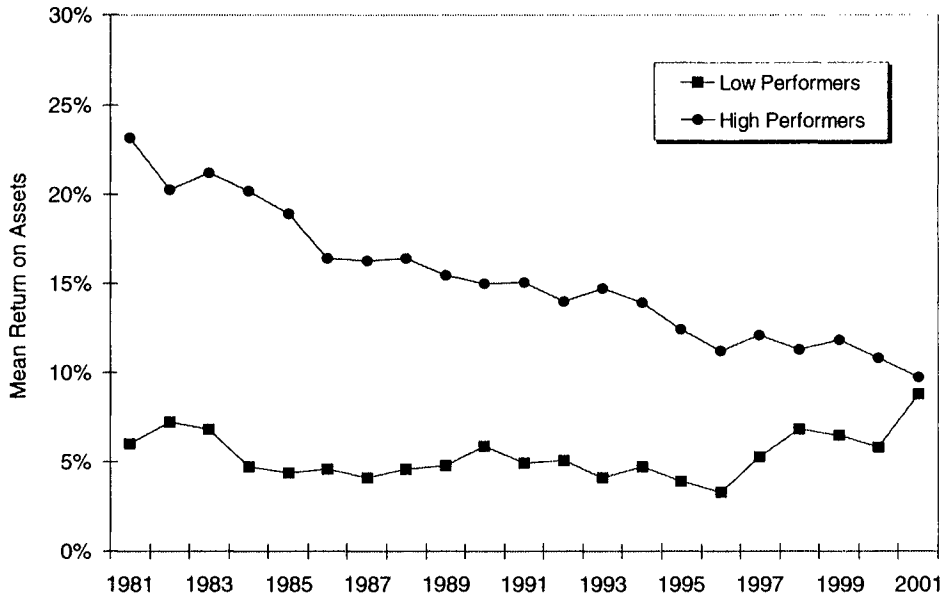

Figure 1. Mean Return on Assets for Low and High Performers in All Sectors, 1980–2001

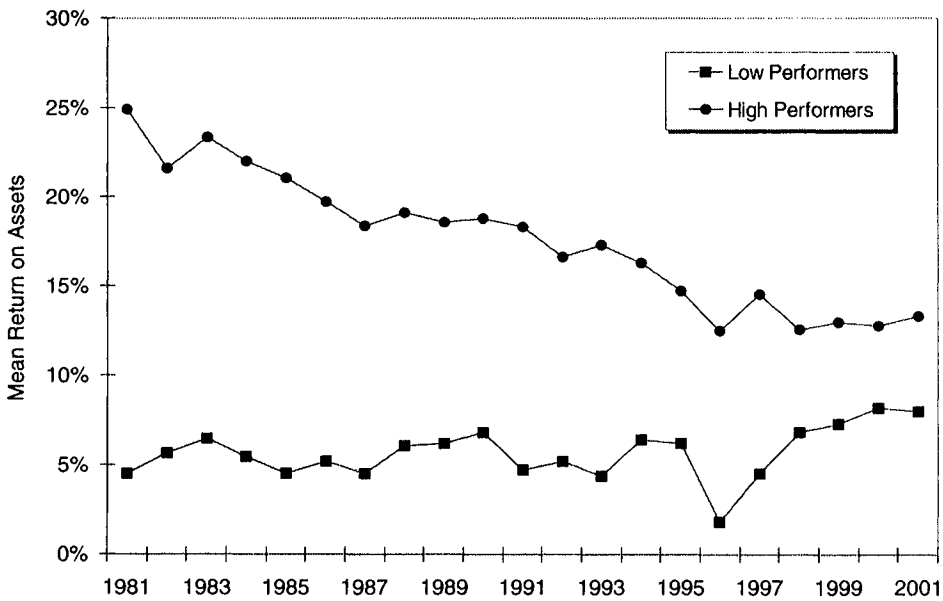

Figure 2. Mean Return on Assets for Low and High Performers in the Processing Sector, 1980–2001

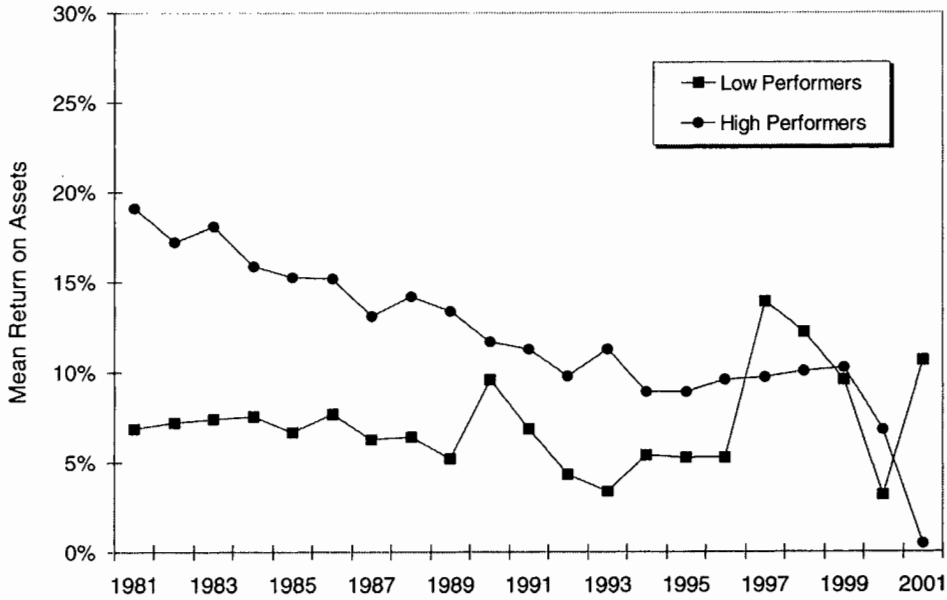

Figure 3. Mean Return on Assets for Low and High Performers in the Wholesale Sector, 1980–2001

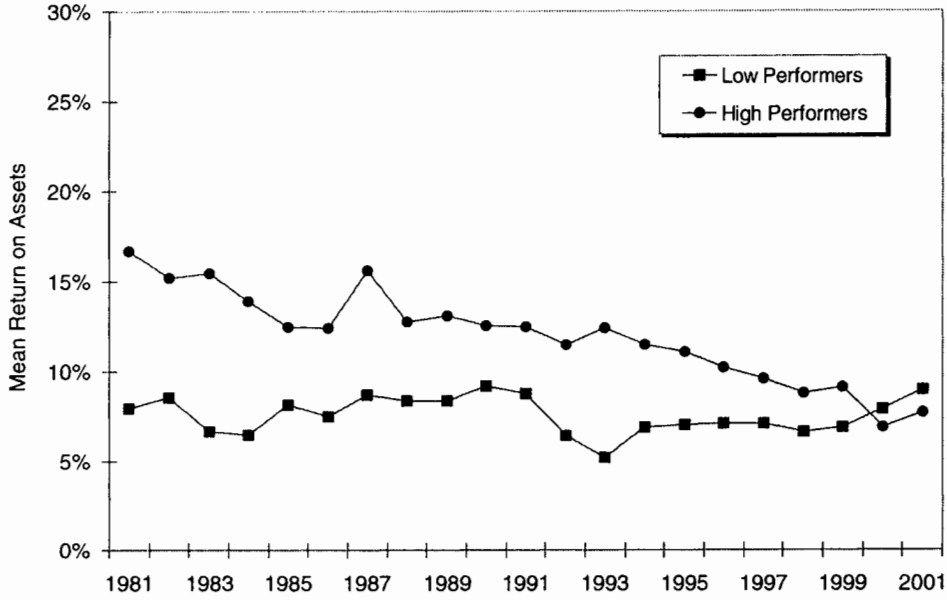

Figure 4. Mean Return on Assets for Low and High Performers in the Retail Sector, 1980–2001

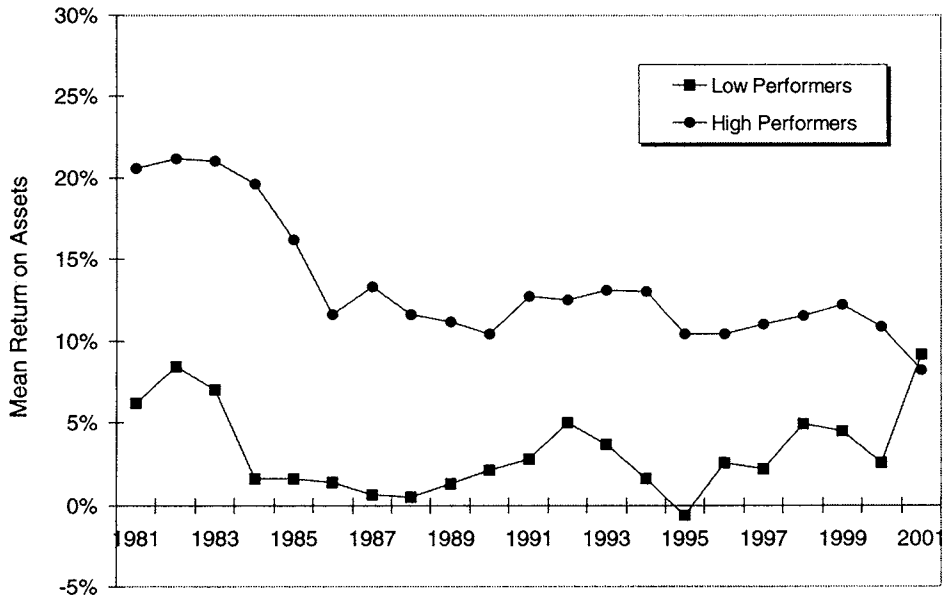

Figure 5. Mean Return on Assets for Low and High Performers in the Restaurant Sector, 1980–2001

The data included in the estimation of sustainability rates consist of 5,854 observations (74% of the screened data set), representing 524 different business segments. These business segments cover 465 corporations, of which 107 are diversified.

As shown in Figures 3–5, the rates for the low performers and high performers cross near the end of the time period. This pattern suggests the wholesale, retail, and restaurant industries went through changes that enabled firms ranking in the low-performer category to improve, and high performers faced an erosion of profitability over this time period. These changes are attributable to industry, year, segment, and corporate effects.

The mean return on assets for the business segments included in the estimation of sustainability rates is 15.5% (5.2%) for high (low) performers. One interesting observation is that the geometric mean of the yearly growth rates was positive for all four sectors with regard to low performers, with an average growth rate across sectors of 1.93%.

Table 1. Percentage of Firms That Were High and Low Performers in 1980 and 2001

		Percentage of Firms in 2001 That Ranked as:	
		High Performers	**Low Performers**
Percentage of Firms in 1980 That Ranked as:	**High Performers**	27%	21%[a]
	Low Performers	18%	34%

[a] This cell denotes that 21% of the firms were high performers (ranked in the top 50%) in 1980, and were low performers (ranked in the bottom 50%) in 2001.

However, the geometric means were all negative for the high performers, with an average growth rate of -4.27%. Thus, return on assets for the high performers eroded almost twice as rapidly as that of the low performers during the 1980–2001 time period. Table 1 shows the percentage of firms that were high performers and low performers at the beginning and end of the time period.

The estimated mean, fixed, and incremental effects for low and high performers by sector are reported in Table 2. All incremental (fixed) effects are estimated to be positive (negative), and 11 of the incremental effects of high performers are larger than the incremental effects of low performers. Industry effects are higher for processing, whereas segment effects are higher for the other three sectors. Industry and corporate effects are larger for high performers on average. For example, high performers in the "all sectors" category have a sum of 0.0695—i.e., the sum of a year effect (-0.0047), industry effect (0.0163), corporate effect (0.0144), and segment effect (0.0436).

Results

Table 3 reports the sustainability rates of business-segment return on assets for low and high performers for the entire food economy and each sector. Within the entire food economy, the sustainability rate of return on assets that deviates from the median for low performers is 20.62%, compared with 34.74% for high performers.

All Sectors

Equality-of-mean *t*-tests were conducted to test the effects between the low and high performers. As shown in Table 3, the means of the sustainability rates of the sum of effects are significantly different (at the 0.10 level) between low and high performers for all sectors combined. One important result is that segment sustainability rates are significantly larger for high performers (22.73%) than for low performers (16.74%) within the entire food economy. Segments with historically above-average return on assets remain highly profitable segments. For example, the SIC 2086 (Bottled and Canned Soft Drinks and Carbonated Waters) segment ranked as a high-performer segment for all but one firm at the beginning and end of the time period.

A second result is that corporate effects are also significantly larger for high performers (8.98%) than for low performers (2.41%), indicating the pattern of diversification is important for high-performing firms. Diversification implies that firms realize economies of scope.

Individual Sector Results

The sum of the sustainability rates is significantly different between high (31.36%) and low (16.08%) performers in the processing sector. Furthermore, the year, industry, and corporate sustainability rates are greater for high performers (27.08%, 24.54%, and 11.11%, respectively) than for low performers (17.93%, 18.16%, and 3.06%, respectively). Clearly, these findings suggest there are important macroeconomic and structural characteristics, and patterns of diversification that enable high-performing processing firms to achieve sustainable rates of return on assets relative to low performers.

For example, Sara Lee, a diversified company, reports its food businesses in SIC segments 2013 (Sausages and Other Prepared Meat Products), 2095 (Roasted Coffee), and 5140 (Groceries and Related Products). All three of these segments were high performers, confirming a successful diversification pattern for Sara Lee during this time period, and a positive corporate effect.

In the wholesale sector, high performers (38.98%) have a significantly greater sum of sustained return on assets effects than do low performers (17.96%). None of the year, industry, and corporate effects were significant in this sector.

No significant differences were found between high and low performers in the retail sector. This suggests that the firms had access to the same technologies, and structural differences did not exist between firms in this sector.

Table 2. Mean, Fixed, and Incremental Effects for Low and High Performers by Sector, 1980–2001

	Year (γ_t)		Industry ($\alpha_{i,t}$)		Corporate[a] ($\beta_{k,t}$)		Segment ($\phi_{i,k,t}$)		SUM	
Sector/Statistic	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**
All Sectors:										
Mean[b]	-0.0044	-0.0047	-0.0085	0.0163	0.0035	0.0144	-0.0238	0.0436	-0.0333	0.0695
Standard Deviation[c]	0.0169	0.0168	0.0613	0.0799	0.0357	0.0509	0.1151	0.1157	0.1252	0.1321
Fixed[d]	-0.1901	-0.1966	-0.1475	-0.1181	-0.1344	-0.0954	-0.1767	-0.0951	-0.1743	-5.4089
Incremental[d]	0.1857	0.1919	0.1390	0.1344	0.1379	0.1098	0.1529	0.1387	0.1410	5.4784
Processing:										
Mean[b]	-0.0046	-0.0045	0.0016	0.0455	0.0052	0.0183	-0.0318	0.0342	-0.0295	0.0936
Standard Deviation[v]	0.0168	0.0170	0.0857	0.0958	0.0417	0.0547	0.1218	0.1268	0.1362	0.1530
Fixed[d]	-0.1838	-0.2018	-0.1269	-0.0822	-0.0914	-0.0930	-0.1618	-0.1121	-0.1631	-0.0896
Incremental[d]	0.1792	0.1974	0.1285	0.1277	0.0967	0.1113	0.1300	0.1463	0.1336	0.1832
Wholesale:										
Mean[b]	-0.0047	-0.0057	0.0019	0.0037	0.0043	0.0081	-0.0176	0.0278	-0.0161	0.0339
Standard Deviation[c]	0.0166	0.0159	0.0643	0.0635	0.0375	0.0341	0.0878	0.0840	0.1016	0.0846
Fixed[d]	-0.1780	-0.1852	-0.0993	-0.1191	-0.0923	-0.1316	-0.1491	-0.1241	-0.1485	-0.1410
Incremental[d]	0.1734	0.1795	0.1012	0.1228	0.0966	0.1396	0.1315	0.1519	0.1324	0.1749
Retail:										
Mean[b]	-0.0026	-0.0045	0.0015	0.0036	0.0010	0.0040	-0.0096	0.0350	-0.0096	0.0381
Standard Deviation[c]	0.0175	0.0167	0.0461	0.0185	0.0295	0.0318	0.0747	0.0659	0.0845	0.0600
Fixed[d]	-0.2349	-0.2047	-0.2437	-0.2279	-0.3857	-0.0895	-0.1861	-0.2083	-0.1720	-0.2072
Incremental[d]	0.2323	0.2002	0.2452	0.2315	0.3867	0.0935	0.1766	0.2434	0.1623	0.2453
Restaurant:										
Mean[b]	-0.0050	-0.0049	-0.0296	-0.0296	0.0023	0.0127	-0.0232	0.0693	-0.0555	0.0474
Standard Deviation[c]	0.0163	0.0165	0.0142	0.0178	0.0322	0.0528	0.1338	0.1126	0.1385	0.1112
Fixed[d]	-0.1811	-0.1875	-0.1453	-0.1451	-0.0839	-0.0905	-0.2008	-0.0132	-0.1988	-18.9173
Incremental[d]	0.1761	0.1826	0.1157	0.1155	0.0862	0.1032	0.1776	0.0825	0.1433	18.9647

[a] Corporate effects are means of all corporations, and not just diversified corporations.
[b] Mean is the mean of estimated effects on each business segment.
[c] Standard deviation is the standard deviation of the estimated difference from the mean.
[d] The mean fixed and incremental components are means of all corporations, and sum to the overall mean.

Table 3. Mean Parameter Estimates, Standard Errors, and R^2 for Low and High Performers by Sector, 1980–2001

	Year (γ_t)		Industry ($\alpha_{i,t}$)		Corporate[a] ($\beta_{k,t}$)		Segment ($\phi_{i,k,t}$)		SUM	
Sector/Statistic	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**
All Sectors:										
Average Estimate[b]	22.73	23.09	21.08	23.71	2.41	8.98*	16.74	22.73*	20.62	34.74*
Standard Error[c]	26.26	24.00	31.25	30.95	7.75	11.14	33.05	29.70	30.06	27.86
Average R^2[d]	50.90	52.78	24.62	22.74	4.91	8.40	22.46	27.22	27.73	36.52
Processing:										
Average Estimate[b]	17.93	27.08*	18.16	24.54*	3.06	11.11*	13.74	17.91	16.08	31.36*
Standard Error[v]	27.24	23.48	30.24	30.17	10.54	14.25	34.08	29.49	29.60	27.83
Average R^2[d]	49.08	53.78	24.90	22.10	6.58	10.47	19.91	24.72	27.12	33.05
Wholesale:										
Average Estimate[b]	26.29	15.44	6.85	12.27	4.43	10.80	6.41	18.45	17.96	38.98*
Standard Error[c]	27.09	24.07	34.19	33.31	8.96	16.42	34.28	34.92	29.80	35.44
Average R^2[d]	46.06	51.41	11.53	16.69	4.56	9.53	18.09	22.74	27.43	35.05
Retail:										
Average Estimate[b]	41.47	26.54	59.83	53.20	3.58	4.48	27.57	33.60	26.57	35.91
Standard Error[c]	22.38	25.11	21.78	22.71	7.77	7.77	29.53	28.44	29.86	27.43
Average R^2[d]	62.02	52.74	65.57	59.95	5.35	4.12	26.93	37.76	25.49	41.06
Restaurant:										
Average Estimate[b]	19.85	16.95	14.61	15.23	0.39	6.03*	20.06	29.23*	24.91	39.19*
Standard Error[c]	26.29	24.55	35.17	34.64	3.80	4.76	32.70	28.80	30.80	25.51
Average R^2[d]	50.54	51.39	12.84	12.35	2.77	5.71	25.51	29.56	29.50	41.87

Notes: An asterisk denotes that the high performer estimate is greater than the corresponding low performer at the 0.10 significance level; *t*-statistics are estimated using the difference between the mean of sustainability estimates for low and high performers.

[a] Corporate effects are means of all corporations, and not just diversified corporations.

[b] The average estimates are means of the estimates on each segment.

[c] The standard error is the mean of the Newey-West standard error of each segment estimate.

[d] This measure is the mean R^2 in the regression on each segment.

In the restaurant sector, corporate and segment sustainability rates are larger for high performers (6.03% and 29.93%, respectively) than for low performers (0.39% and 20.06%, respectively). High-performing firms in the same business sector had a significantly greater competitive advantage than low-performing firms.

Across and Between Sectors

Low and high performers' industry and business-segment sustainability rates were tested among the four sectors by using *t*-statistics. Retail industry and business-segment sustainability rates were significantly greater than those of the other three sectors for low and high performers. Industry sustainability rates for the processing sector were greater than for the wholesale and restaurant sectors. Retail was greater than processing and wholesale for business-segment sustainability rates, and the restaurant sector was greater than the wholesale sector for sustainability rates.

Conclusions

Four important results have emerged from this research:

- First, industry incremental effects (as seen in Table 2) and sustainability estimates (as reported in Table 3) are not significantly different between low and high performers, except in the processing sector. This finding suggests that industry shocks impacting the food economy between 1980 and 2001 had the same effect on both low and high performers. However, the processing sector has structural characteristics that are conducive to high-performing firms, and these are likely to be significant barriers to entry for new firms. This result points to opportunities for further research in identifying these structural characteristics. Managers of processing firms are likely to undertake strategic decisions intended to maintain these barriers to entry. These could include making investments in technologies that reduce processing costs or undertaking risk-management strategies that enable them to purchase inputs at lower prices. Similarly, some processing firms have long-standing relationships with suppliers and buyers which also act as barriers to entry.

- Second, on average, high performance has been more sustainable than low performance within the food economy, and positive incremental effects have been generally larger for high performers than for low performers. The competitive process that causes above- and below-average return on assets to erode toward the median has been slower for high performers than for low performers. High performers were able to maintain a larger portion of positive incremental effects. Thus, benefits from moving first with an innovation or technological breakthrough are more likely to occur with high performers. Managers of high-performing firms are likely to invest more in research and development, enabling them to discover these innovations or technological breakthroughs.

- Third, within the entire food economy, the corporate and segment sustainability rates were larger for high performers than for low performers. This implies corporate and segment effects have a larger impact on high performers' return on assets than those of low performers. Corporate and business-segment effects were the largest source of sustainability across all four sectors. This was especially true in the restaurant sector, suggesting the pattern of diversification was more successful for high performers. In addition, this finding reveals that high performers possessed other superior business traits, such as better management of inputs or organizational design, relative to low performers. Clearly, managers of high-performing firms are better at achieving the benefits of economies of scope across their business segments.

- Fourth, in contrast, there is no significant difference between sustainability rates of high and low performers within the retail sector, suggesting innovations and other means of competitive advantage were easily imitated and had a similar effect on both low and high performers. However, high performers in the retail sector had significantly greater industry, business-segment, and total-sum sustainability rates compared to the other three sectors, indicating the retail sector has important characteristics that merit further research.

Based on these findings, it is important to further analyze the sustainability of return on assets within the food economy by sector. Moreover, general conclusions about the food economy may not apply to specific sectors. And, results obtained from analyzing firms within the entire economy may not be applicable to the food economy or the individual sectors within it.

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Appendix: Further Derivation of the Theoretical Model

The theoretical model requires subtracting the time means of equations (A1)–(A5) from themselves:

(A1) $r_{i,k,t} = h_{i,k} + \rho_{i,k} r_{i,k,t-1} + \psi_{i,k,t}$,

(A2) $\gamma_{i,k,t} = h^{\gamma}_{i,k} + \rho_{YR,i,k}\gamma_{i,k,t-1} + \lambda_{i,k,t}$,

(A3) $\alpha_{i,k,t} = h^{\alpha}_{i,k} + \rho_{IN,i,k}\alpha_{i,k,t-1} + \nu_{i,k,t}$,

(A4) $\beta_{i,k,t} = h^{\beta}_{i,k} + \rho_{CP,i,k}\beta_{i,k,t-1} + \xi_{i,k,t}$,

and

(A5) $\phi_{i,k,t} = h^{\phi}_{i,k} + \rho_{BS,i,k}\phi_{i,k,t-1} + \kappa_{i,k,t}$,

where the intercept term is a function of the fixed effect and the rate of sustainability, and where

$$r_{i,k,\underline{t}} = \left(\frac{1}{T}\right)\sum_{t=1}^{T} r_{i,k,t}$$

and

$$r_{i,k,\underline{t-1}} = \left(\frac{1}{T}\right)\sum_{t=0}^{T-1} r_{i,k,t}.$$

For example, the intercept term in equation (A5) is $(1 - \rho_{BS,i,k})f^{\phi}_{i,k}$. Similar interpretations of the intercept terms in equations (A1)–(A4) can be made.

Rural Small Business Trade Credit: A Paradox

Cole R. Gustafson

Abstract

This article examines trade credit practices of rural small business firms. The results show that these firms borrow money and then re-lend it to others in the form of trade credit. There is a strong direct relationship between various forms of debt held by these firms and their level of accounts receivable (e.g., trade credit extended to customers). The actual level of re-lending varied among firms depending on their adoption level of computer usage for cash management and credit services. Accounts receivable balances were also dependent on sales levels, costs of doing business, and other income.

Key words: credit, finance, rural small business, trade

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Credit granted by a selling firm to finance another firm's purchase of the seller's goods, commonly referred to as trade credit, remains the single largest source of short-term business credit for small U.S. firms (Petersen and Rajan, 1997). Recent studies of small food manufacturing firms (Gustafson, 2003) and rural small businesses (Gustafson, 2004), many of which are rural and agriculturally related, show that trade credit comprises nearly one-fourth of total financing for these firms as well.

Persistent high levels of trade credit appear to be a paradox in the face of highly developed U.S. financial markets. Why do rural small business firms continue to act as financial intermediaries—a role usually reserved for financial institutions? Moreover, despite its importance, trade credit receives far less attention in the agricultural finance literature than longer term sources of credit. Yet, when a firm's suppliers begin to demand cash on delivery, it is often a key signal the firm faces impending financial difficulty and bankruptcy.

This study utilizes Federal Reserve Bank small business survey information to compare and contrast trade credit practices of rural small business firms. The survey, conducted in 1998, provides robust information on the financing of small businesses including an overview of the firms' organization, financial characteristics, and credit use (Bitler, Robb, and Wolken, 2001). An appealing feature of this survey is the delineation of metro and rural (nonmetro) respondents, based on whether the respondent lives in a metropolitan statistical area (MSA) or not.

The specific objectives of the study are to first identify which rural small businesses extend trade credit. Next, various characteristics of rural small businesses are related to the quantity of trade credit borrowed and lent to others. These characteristics include firm organization, financial structure, profitability, credit history, concentration of competing lenders, and use of computer technology.

Results of this study show that, in spite of highly developed U.S. financial markets, rural small businesses continue to act as financial intermediaries by obtaining credit from financial institutions and then re-lending it to their customers in the form of trade credit—providing evidence that the paradox does indeed exist. If rural credit markets were efficient, rural small businesses would normally have a difficult time competing with financial institutions' specialized methods of credit analysis and lower cost sources of funds.

Several public policy efforts have attempted to increase the efficiency of delivery and availability of credit to rural small businesses (e.g., Farm Credit System, Small Business Administration), and lessen dependence on trade credit. Lack of participation in these programs may warrant a review of their breadth and operation. Moreover, if re-lending is a significant component of rural small business activity, it adds a unique component of risk that is separate and distinct from their core business enterprises. Equity holders and debt providers may need to exert more oversight when monitoring financial performance. New firms seeking to compete with rural small businesses must consider the jointness of credit and purchase decisions.

The following sections of this article provide a background on trade credit, and describe the 1998 Federal Reserve's Survey of Small Business Finances including the survey's history, content, sampling procedure utilized, and procedures for access. An overview of rural small business trade credit is then presented with comparisons made between firms that receive and extend credit.

Role of Trade Credit in Small Business Finance

Trade credit is the primary source of finance in undeveloped countries where limited financial intermediation exists (Demirgüc-Kunt and Maksimovic, 2001). However, it is an important component source of financial capital in developed countries as well. Rajan and Zingales (1995) found that accounts payable (AP) as a percentage of total credit ranged from 11.5% in Germany to 17% in France, with Canada (13.3%), the United Kingdom (13.7%), Italy (14.7%), the United States (15%), and Japan (15.4%) falling in between. Accounts receivable (AR) as a percentage of total assets in these countries ranged from 13% in Canada to 29% in France and Italy. Usage of trade credit would likely be higher among small and rural businesses where credit access is more difficult.

The importance of trade credit to commercial firms has been noted by several authors, including the early works of Jaffee (1971) and Meltzer (1960). However, Petersen and Rajan (1997) were among the first to quantitatively investigate the importance of trade credit to both large and small businesses.[1] Data for their analysis were obtained from both the Federal Reserve Bank's Survey of Small Business Finances and Compustat. In general, Petersen and Rajan found that firms strongly prefer to borrow from a bank, if bank credit is available. Firms with unused bank credit had significantly lower AP (i.e., they use less trade credit). Also, firms with long-term relationships with a bank use less trade credit. Interestingly, accounts receivable balances were found to be positively correlated with firm age and size, i.e., they were suppliers

[1] A small business is defined in the Survey of Small Business Finances as a firm with less than 500 employees. This definition is used throughout the remainder of this study.

of credit. In fact, larger firms were found to have easier access to external finance and in turn acted as financial intermediaries by extending trade credit to other smaller firms. Although Petersen and Rajan studied small businesses, they did not differentiate between metro and rural firms.

The Persistence of Trade Credit in Developed Financial Markets

These prior studies have failed to explain the paradox of why trade credit exists in highly developed financial markets. Several theories, discussed below, have been advanced to explain the anomaly.

Risk and Macroeconomic Cycles

Nilsen (2002) and Lang and Nakamura (1995) found that bank credit availability varies depending on macroeconomic conditions. Riskier firms often seek additional trade credit during periods of economic tightness in an effort to maintain operations. Nilsen (2002) reports that in tight conditions, trade credit increases for small firms, but not for large firms (those having greatest access to bank loans and outside sources of finance). Rural small business firms are likely to be viewed as riskier and consequently require additional trade credit because of their concentration in a single sector (agriculture) and rural location.

Principal/Agent Theory

If markets are efficient, financial institutions would be expected to use their competitive advantages of lower source fund costs and specialized credit risk assessment to lend directly, even in tight macroeconomic conditions. Recent explanations have focused on principal/agent issues and monitoring. Burkhart and Ellingsen (2002) suggest that trade credit is tied more closely to tangible assets, which can be tracked and monitored. Monies obtained from a financial institution are fungible and more easily diverted. Extension of trade credit is related to a physical quantity of goods, and repayment is expected when they are sold. Thus, tracking is easier. In risky times, trade credit may be viewed as a credible commitment not to divert funds to unprofitable purposes. Even though financial institutions have lower cost funds, total costs are higher because fund usage cannot be monitored as efficiently.

Firms receiving trade credit provide early warning signals to suppliers that are unobservable to financial institutions. Suppliers who offer two-part trade credit view payments beyond the discount period as a sign of financial difficulty (Ng, Smith, and Smith, 1999). Petersen and Rajan (1994) found that 90% of firms take advantage of early payment discounts.

Financial institutions may delegate the monitoring of risky firms to trade credit suppliers. When conditions improve, close monitoring is less important, and financial institutions can increase their share of financing working capital for riskier firms. Moreover, firms and trade credit suppliers have incentives to collude against financial institutions. Suppliers benefit from the sale, and risk of default is shifted to the financial institution (Biais and Gollier, 1997).

Terminating shipments, and thus trade credit when nonpayment occurs, is a strong means of enforcing repayment and monitoring—especially if a supplier provides the business with a product that has no close substitutes. But, businesses provide continued and growing demand for suppliers' goods. Thus, mutual long-term relationships are important to trade credit. Ng, Smith, and Smith (1999) found suppliers are willing to extend discount periods for long-term customers, thus refuting two-part trade credit as a signal of financial risk.

Transaction Costs/Price Discrimination

Several other theories have been advanced to explain use of trade credit over financial

institution credit.[2] Frank and Maksimovic (1998) argue that trade credit suppliers may have a comparative advantage in liquidating inventory in cases of default, thereby lowering transaction costs. Ferris (1981) shows that transaction costs are reduced in the presence of uncertainty about delivery times and production needs because trade credit reduces a firm's need to hold precautionary balances. Finally, as noted by Brennan, Maksimovic, and Zechner (1998), trade credit allows firms to engage in price discrimination by combining sales with credit.

In summary, the literature suggests several reasons why trade credit persists when small businesses also have access to financial institution loans. The opportunity to (*a*) more closely monitor a firm's use of credit proceeds, (*b*) lower transaction costs if default occurs, and (*c*) tie credit with product sales may partially explain observed firm behavior. Small business finances survey data are used to identify the extent to which firms utilize trade credit, to determine if trade credit use varies among firms with differing financial and business characteristics, and to assess whether use is more prevalent among firms with poorer credit histories.

The Survey of Small Business Finances

The Survey of Small Business Finances (SSBF) is used in this study to empirically test the relationships outlined above. The SSBF is conducted by the Federal Reserve Bank and collects demographic and financial information from 3,561 for-profit, nonfinancial, nonfarm small businesses (less than 500 employees) who were in business in the United States at the end of 1998.[3] Similar surveys have been conducted in 1987 and 1993.

Information collected in the survey includes the following:

- Demographic information on the owners and characteristics of the firm including SIC, MSA, and Dun & Bradstreet industry classifications;
- Inventory of the firm's deposit and savings accounts, leases, credit lines, mortgages, loans, and other financial services (for each financial service, the supplier is identified);
- Characteristics of financial service suppliers including type (e.g., bank, individual), method of conducting business, patronage, and reasons for choosing source;
- Experience in applying for credit in the past three years;
- Experience with trade credit and equity injections;
- Firm's income and balance sheet; and
- Credit history, credit scores for both firm and owners, and Herfindahl index of concentration.

Sampling was done according to a two-stage stratified random sample. In the first stage of the SSBF survey, a sample was drawn from the Dun & Bradstreet Market Identifier file, which represents approximately 93% of full-time business activity in the United States. In the second stage, small businesses with more than 20 employees and minority-owned firms were over-sampled to ensure their numbers would be sufficient for statistical testing. An overall response rate of 33% was obtained. Sample weights for each observation are included in the public data set.

[2] One reviewer of this article suggests there may be a historical reason for this practice. Many cooperatives have been created to fill market gaps in rural areas. Cooperatives often found they had to extend credit with product sales. Because farms and businesses could not obtain credit at favorable terms, cooperatives extended financing as well. Once institutionalized, cooperative boards have had difficulty changing policy.

[3] Working papers, methodological documentation, codebooks, and full public data sets (SAS or PDF) are available online at: http://www.federalreserve.gov/pubs/oss/oss3/nssbftoc.htm.

Bitler, Robb, and Wolken (2001) summarize key survey findings. Over 83% of the small businesses had less than 10 employees and over one-half were organized as sole proprietorships. The primary activity for 43% of the firms was business or professional services. Commercial banks were the primary supplier of financial services, and 55% of the surveyed businesses reported having loans, capital leases, or lines of credit at year end. Trade credit was used by 60% of small businesses in 1998, but interest rates were quite high; 2% a month was not uncommon. Three-fourths of the firms used computers, primarily for accessing the internet, inventory management, and bookkeeping. Data from this survey have also been used to explore lending practices of rural banks involved in mergers (Walraven, 1999) and portfolio decisions of small agribusinesses (Holmes and Park, 2000).

Regression Analysis

Ordinary least squares regression techniques are employed to estimate the influence of key financial variables and measures of technology on utilization of trade credit by rural small businesses. Again, since these firms are located primarily in rural areas and are either directly or indirectly affected by economic prosperity in agriculture, it is assumed they are representative of rural small business firms.

Two separate equations are estimated, one in which the firm's accounts receivable (*AR*) balance is the dependent variable and the other where the firm's balance of accounts payable (*AP*) is the dependent variable. The first equation represents the degree to which rural small businesses extend trade credit to other firms and farmers, whereas the second equation delineates important factors affecting a rural small business firm's demand for trade credit.

The variables contained in each equation arise directly from the discussion of the SSBF survey above or have been suggested by others as being important to rural small business credit decisions. The general form of each regression model is expressed as:

$$AR_t \text{ or } AP_t = B_0 + \sum_{k=1}^{32} B_k X_{k,t} + \varepsilon_t,$$

where AR_t and AP_t are the dependent variables defined above, X_1–X_5 are general financial measures of performance and size, X_6–X_{15} represent liquidity and other forms of credit available, X_{16}–X_{21} quantify the firm's use of computers for various financial services, X_{22}–X_{26} measure the firm's use of other financial services, X_{27} is the firm's Dun & Bradstreet credit score, X_{28}–X_{31} measure the firm's historical financial stress, and X_{32} is the Herfindahl measure of bank concentration. Plausible, anticipated relationships between *AR* or *AP* and the respective variables are discussed in the next section.

Model Relationships

The first set of explanatory variables (X_1–X_5) is derived from financial information elicited from each firm in the survey. A positive relationship between both *AR* and *AP*, and total assets (X_1) is expected. As a measure of overall firm size and business activity, both *AR* and *AP* would be expected to increase as total assets increase. For the same reason, positive relationships between *AR* and *AP* and total investments (X_2) are also expected as they are indicators of overall firm expansion and activity. Likewise, positive relationships with total sales (X_3) are expected. Higher sales among firms of relatively similar size indicate greater turnover and efficiency.

The relationship between cost of doing business (X_4) and *AR* is unknown, but a positive relationship with *AP* is expected. Inefficient firms with relatively higher costs would be expected to have difficulty paying bills, leading to higher *AP*. Other income (X_5) is expected to increase a firm's ability

to extend *AR* (a positive relationship) and reduce *AP* (a negative relationship).

If firms acquire debt with the expectation of re-lending it to others in the form of trade credit, a positive relationship between total liabilities (X_6) and *AR* would be expected. Total liabilities (X_6), net of *AP*, would be expected to be positively related to *AP* also. If total firm liabilities are high, *AP* would be hypothesized to increase correspondingly because it is a form of debt as well.

Checking (X_7) and savings (X_8) account balances represent sources of funds and are anticipated to be positively related to *AR* and negatively related to *AP*. As available funds increase, firms have greater capacity to extend *AR* and pay down *AP*.

Variables X_9–X_{15} represent different types of firm debt, ranging from short-term credit card to long-term mortgages. As hypothesized above with total liabilities, all of these are expected to be positively related to *AR* and *AP*. With X_9–X_{15} and total liabilities both in the estimated equation, there is a risk of multicollinearity. However, X_9–X_{15} do not comprise all liabilities, as several minor categories of debt are not delineated in the SSBF survey.

Use of computers for various financial and office functions is measured by binary variables X_{16}–X_{21} (1 = yes, 2 = no). Use of computer technology is presumed to enable the firm to improve *AR* and *AP* management. Both would be expected to positively increase as the firm becomes able to manage and extend more trade credit to others (*AR*) and take advantage of more credit available to itself (*AP*).

Other financial services used by the firms are quantified by binary variables X_{22}–X_{26} (1 = yes, 2 = no). Like use of computers, greater use of technology is expected to improve *AR* and *AP* management, leading to positive increases in both.

The firm's financial position is summarized by variables X_{27}–X_{31}. DB credit score (X_{27}) is the credit score determined by Dun & Bradstreet (1 = best risk, 5 = high risk). X_{28}–X_{31} are binary variables (1 = yes, 2 = no) indicating if the firm has been denied trade credit, been bankrupt in the last seven years, is presently delinquent on payments, or has not applied for credit because it feared denial. Firms with greater financial strength are expected to offer greater *AR*. Firms in financial difficulty likely have increased *AP*, an inverse relationship.

The final variable, X_{32}, is the Herfindahl index, a measure of bank concentration that is derived by summing squared market shares × 10,000. Increased bank competition is hypothesized to lead to a greater breadth of financial services, products, and intermediation. With more competition, banks have greater incentive to supply a range of financial products to risky small businesses. Thus, a positive relationship between concentration and both *AR* and *AP* is expected.

Econometric Results

The studies reviewed earlier predict that rural small businesses obtain credit from financial institutions and then re-lend it to their customers in the form of trade credit (e.g., accounts receivable). In this section, that theory is tested using the empirical methods described above and SSBF data from 779 rural small business firms.

To aid interpretation of model results, means and standard deviations of variables contained in the sample of 779 rural small businesses that were used to estimate the empirical model are presented in Table 1. These data are weighted with SSBF sample weights to more accurately reflect minority populations. Firms in the sample had average accounts receivables of $49,470 and accounts payable of $43,465. Large standard deviations for these variables denote large variation among individual firms in the sample.

Table 1. Summary Statistics of Variables in the Rural Small Business Data Set

Variable	/ Description	Mean (n = 779)	Standard Deviation
AP	Accounts payable ($000s)	43.5	16.0
AR	Accounts receivable ($000s)	49.5	8,929.1
X_1	Total assets ($000s)	307.2	59,737.1
X_2	Total investments ($000s)	19.5	21,297.9
X_3	Total sales for current FY ($000s)	664.1	87,148.6
X_4	Total cost of doing business ($000s)	561.1	80,049.9
X_5	Other income ($000s)	11.0	7,717.9
X_6	Total liabilities ($000s)	194.2	44,867.1
X_7	Checking balance year end ($000s)	27.0	7,543.9
X_8	Savings balance year end ($000s)	7.8	1,807.8
X_9	Personal credit card average monthly charge ($)	428.25	86.0
X_{10}	Business credit card average monthly charge ($)	383.45	70.1
X_{11}	Amount owed on credit line ($000s)	18.7	6,584.7
X_{12}	Mortgage principal owed ($000s)	34.9	13,108.2
X_{13}	Equipment principal owed ($000s)	11.2	9,703.6
X_{14}	Stockholder loans principal owed ($000s)	16.0	10,244.2
X_{15}	Principal owed on other loans ($000s)	11.2	4,651.1
	Variables X_{16} through X_{26} are binary variables, where 1 = yes and 2 = no		
X_{16}	Computers used for PC banking	1.23	34.70
X_{17}	Computers used for e-mail	1.08	26.38
X_{18}	Computers used for internet sales	1.09	32.77
X_{19}	Computers used for credit applications online	1.26	35.05
X_{20}	Computers used for administration	1.08	24.98
X_{21}	Computers used for accounting/bookkeeping	1.08	23.67
X_{22}	Use transaction services	1.62	17.96
X_{23}	Use cash management services	1.96	7.58
X_{24}	Use credit-related services	1.96	7.58
X_{25}	Use trust services	1.91	10.64
X_{26}	Use brokerage services	1.97	6.42
X_{27}	DB credit score rank, determined by Dun & Bradstreet (1 = best risk, 5 = high risk)	2.93	36.04
	Variables X_{28} through X_{31} are binary variables, where 1 = yes and 2 = no		
X_{28}	Suppliers ever denied trade credit	1.96	6.93
X_{29}	Bankruptcy in past seven years	1.98	5.69
X_{30}	Delinquent on business obligations	1.26	27.62
X_{31}	Didn't apply for credit fearing denial	1.79	14.96
X_{32}	Herfindahl index (a measure of bank concentration)	2.84	13.47

Accounts receivable represents less than 16% of total assets. However, accounts payable comprises 22% of total liabilities. The greater importance of accounts payable as a source of credit is not unexpected, given the difficulty experienced by rural small businesses in accessing long-term credit (Gustafson, 2004). Modest amounts of other credit are used (variables X_9–X_{15}). Variables X_{16}–X_{26} and X_{28}–X_{31} are binary variables (1 = yes, 2 = no). Rural small businesses use computers for e-mail, internet, administration, and bookkeeping. Although few rural small businesses have been denied trade credit or have been in bankruptcy in the past seven years, the majority have been delinquent on business obligations.

Accounts Receivable

Table 2 presents ordinary least squares (OLS) regression results for the *AR* model shown in the general-form equation presented earlier. In essence, the variables presented in Table 1 (X_1–X_{32}) are regressed on each firm's level of accounts receivable. The estimated model has an *F*-value of 24.93 and adjusted R^2 of 0.50 with 743 degrees of freedom (d.f.), a good fit for firm-level, cross-sectional data.

The dependent variable, each firm's *AR*, is found to be statistically related to several independent variables. The coefficients of total liabilities (X_6), mortgage principal owed (X_{12}), and stockholder loans (X_{14}) are statistically significant. It is interesting to note that these are all longer term sources of credit, which may provide continuity to a firm's *AR* policy. Further, the magnitude of the coefficients suggests cautionary use of these credit forms for re-lending, as the largest rate is 7%. For example, a $1 increase in total liabilities results in only a $0.03 increase in *AR*. All are positive relationships as hypothesized.

Also as expected, *AR* is positively related to sales (X_3), investments (X_2), other income (X_5), and checking account balances (X_7). As firm activities and available funds expand, *AR* appears to increase as well. A firm's cost of doing business (X_4) is positively related to *AR*, but this relationship was not hypothesized a priori.

Use of computers for credit applications online (X_{19}) is positively related to *AR*, as expected. The use of cash management (X_{23}) and credit-related services (X_{24}) are negatively related to increased *AR*, an unexpected result. Interestingly, levels of financial market competition, the firm's credit rating, and prior financial history are not statistically related to *AR*. Evidently, firms receiving *AR* are not concerned about the firm's health as long as they are able to receive trade credit.

Accounts Payable

Table 3 presents similar OLS regression results for the model with *AP* as the dependent variable. The estimated model has an *F*-value of 35.51 and adjusted R^2 of 0.59 with 745 d.f., another good fit for firm-level, cross-sectional data.

The dependent variable, each firm's *AP*, is found to be statistically related to several independent variables, many of which were also important in the *AR* equation estimated above. *AP* is positively related to total sales (X_3) and cost of doing business (X_4). As sales increase, *AP* increases by 3.3%. Moreover, as business costs increase, *AP* positively increases as a portion of additional costs are financed on trade credit extended by others.

Checking (X_7) and savings (X_8) account balances, as well as other income (X_5), represent fund sources that may mitigate the need for *AP*. Thus, a negative relationship is found between these variables and *AP*. As hypothesized, when available funds increase, firms pay down *AP* in order to reduce the finance charges associated with trade credit.

Business credit cards (X_{10}), a credit line (X_{11}), a mortgage (X_{12}), and other loans (X_{15}) appear to be substitutes for *AP*.

Table 2. Factors Affecting Rural Small Business Accounts Receivable Levels

Variable	/ Description	Parameter Estimate	Standard Error
	Intercept ($000s)	7,393.40**	165.60
X_1	Total assets	-0.0009	0.01
X_2	Total investments	0.02*	0.01
X_3	Total sales for current FY	0.02**	0.01
X_4	Total cost of doing business	0.01*	0.01
X_5	Other income	0.23**	0.03
X_6	Total liabilities	0.03**	0.01
X_7	Checking balance year end	0.10**	0.04
X_8	Savings balance year end	-0.08	0.14
X_9	Personal credit card average monthly charge	-1.68	2.70
X_{10}	Business credit card average monthly charge	3.19	3.38
X_{11}	Amount owed on credit line	0.02	0.05
X_{12}	Mortgage principal owed	0.07**	0.02
X_{13}	Equipment principal owed	-0.03	0.03
X_{14}	Stockholder loans principal owed	0.04*	0.02
X_{15}	Principal owed on other loans	0.02	0.05
	Variables X_{16} through X_{26} are binary variables		
X_{16}	Computers used for PC banking ($000s)	-74.10	25.80
X_{17}	Computers used for e-mail ($000s)	27.20	18.10
X_{18}	Computers used for internet sales ($000s)	15.10	11.30
X_{19}	Computers used for credit applications online ($000s)	73.90**	28.90
X_{20}	Computers used for administration ($000s)	-6.20	19.20
X_{21}	Computers used for accounting/bookkeeping ($000s)	-13.20	20.30
X_{22}	Use transaction services ($000s)	13.50	13.40
X_{23}	Use cash management services ($000s)	-217.50**	31.80
X_{24}	Use credit-related services ($000s)	-143.20**	31.50
X_{25}	Use trust services ($000s)	30.40	23.10
X_{26}	Use brokerage services ($000s)	-45.60	37.10
X_{27}	DB credit score rank ($000s)	-9.30	6.60
	Variables X_{28} through X_{31} are binary variables		
X_{28}	Suppliers ever denied trade credit ($000s)	7.01	34.00
X_{29}	Bankruptcy in past seven years ($000s)	-10.70	41.30
X_{30}	Delinquent on business obligations ($000s)	-173.59	8.80
X_{31}	Didn't apply for credit fearing denial ($000s)	-56.60	16.90
X_{32}	Herfindahl index ($000s)	5.00	17.20
Adjusted R^2 = 0.4963; F-statistic = 24.93			

Note: Single and double asterisks (*) denote significance at $P < 0.05$ and $P < 0.01$, respectively.

Table 3. Factors Affecting Rural Small Business Accounts Payable Levels

Variable	/ Description	Parameter Estimate	Standard Error
	Intercept ($000s)	-297.70	268.60
X_1	Total assets	0.002	0.01
X_2	Total investments	-0.004	0.02
X_3	Total sales for current FY	0.03**	0.01
X_4	Total cost of doing business	0.07**	0.01
X_5	Other income	-0.31**	0.06
X_6	Total liabilities	0.43	0.02
X_7	Checking balance year end	-0.14*	0.06
X_8	Savings balance year end	-0.19	0.22
X_9	Personal credit card average monthly charge	-2.32	4.38
X_{10}	Business credit card average monthly charge	-9.16*	5.47
X_{11}	Amount owed on credit line	-0.44**	0.08
X_{12}	Mortgage principal owed	-0.33**	0.04
X_{13}	Equipment principal owed	0.02	0.04
X_{14}	Stockholder loans principal owed	-0.05	0.04
X_{15}	Principal owed on other loans	-0.26**	0.09
	Variables X_{16} through X_{26} are binary variables		
X_{16}	Computers used for PC banking ($000s)	-96.70*	41.80
X_{17}	Computers used for e-mail ($000s)	57.80*	29.30
X_{18}	Computers used for internet sales ($000s)	14.40	29.20
X_{19}	Computers used for credit applications online ($000s)	-9.10	46.90
X_{20}	Computers used for administration ($000s)	43.00	31.10
X_{21}	Computers used for accounting/bookkeeping ($000s)	23.00	32.80
X_{22}	Use transaction services ($000s)	-9.00	21.70
X_{23}	Use cash management services ($000s)	-842.27	51.60
X_{24}	Use credit-related services ($000s)	-117.30*	51.00
X_{25}	Use trust services ($000s)	-16.80	37.50
X_{26}	Use brokerage services ($000s)	8.50	60.10
X_{27}	DB credit score rank ($000s)	-489.34	10.70
	Variables X_{28} through X_{31} are binary variables		
X_{28}	Suppliers ever denied trade credit ($000s)	14.00	55.00
X_{29}	Bankruptcy in past seven years ($000s)	47.70	66.90
X_{30}	Delinquent on business obligations ($000s)	20.50	14.20
X_{31}	Didn't apply for credit fearing denial ($000s)	-19.10	27.30
X_{32}	Herfindahl index ($000s)	-2.40	27.90

Adjusted $R^2 = 0.59$; F-statistic = 35.51

Note: Single and double asterisks (*) denote significance at $P < 0.05$ and $P < 0.01$, respectively.

Increases in any of these credit forms reduce *AP*, the inverse relationship that was hypothesized. If a firm had a difficult time obtaining financing from any of these credit sources, its *AP* level would be expected to increase. Notice that the largest (absolute value) coefficient is attached to credit line (X_{11}), implying this is the closest substitute, but far from perfect.

Use of computers for PC banking (X_{16}) and for e-mail (X_{17}) have a mixed impact on *AP*. The coefficient for PC banking is as hypothesized—increased adoption of computers for PC banking leads to greater *AP* balances (recall, this is a binary, 1 = yes/2 = no, variable). However, use of computers for e-mail leads to an unexpected inverse relationship. Use of a credit service (X_{24}) also confirms the hypothesized relationship that increased levels of financial services lead to greater *AP*.

None of the other measures of bank concentration, credit score, or financial stress are significantly related to *AP*. Again, it appears firms perform few credit checks of past financial history before providing trade credit.

Conclusion

Do rural small businesses obtain credit from financial institutions and then re-lend it to others in the form of trade credit? Empirical results from this analysis of rural small business finances suggest the answer is yes. As predicted by the theory developed in the first part of this paper, there is a strong positive relationship between various forms of debt held by these firms and their level of accounts receivable (e.g., trade credit extended to customers). The actual level of re-lending varied among firms depending on their adoption level of computers for cash management and credit services. Accounts receivable balances were also dependent on sales levels, cost of doing business, and other income. The most important source of funds for re-lending was obtained from mortgages and stockholder loans. These fund sources provide continuity in trade credit availability.

The results also identify key factors affecting demand of trade credit extended to rural small businesses by other firms (accounts payable). A strong inverse relationship exists between *AP* and other credit sources, indicating they are substitutes. Greater availability of credit from mortgages, other loans, and credit lines reduces demand for *AP*. However, they are not perfect substitutes. Like *AR*, *AP* demand varies with level of sales, cost of doing business, other income, and adoption of technology.

Results shed some light on the paradox raised at the beginning of this article. First, empirical evidence suggests that trade credit is still a relatively important source of financial capital to rural small businesses. Although greater availability of credit from financial institutions lessens demand for trade credit, it is not a perfect substitute. Thus, trade credit persists, even within developed financial markets. Second, despite evidence of troubled financial histories as indicated by past delinquencies among rural small businesses included in the sample, measures of financial stress, credit rating, and delinquency were unrelated to trade credit decisions. This finding would imply a lack of interest in monitoring a firm's use of trade credit—a key argument underlying the principal/agent theory. Instead, a strong relationship exists between sales/other sources of income and trade credit. It appears that the paradox continues because of the lower transaction costs of liquidation and price discrimination afforded by jointly tying credit with product sales.

Although the SSBF survey information is robust, the selection of rural small businesses employed in the study is an imperfect definition of agribusiness. Moreover, these national data do not capture the unique competitive environments, statutory regulations, and

geographic idiosyncrasies that arise in local financial markets. A dedicated survey overcoming these limitations may provide greater insight and reliability.

This study has several implications. First, re-lending on the part of rural small businesses may alter the riskiness of these firms, depending on their ability to appraise creditworthiness and the level/distribution of net returns from the re-lending activity. Equity holders, profit-sharing employees, and communities that rely on the firm's economic activity may have interest in greater disclosure of re-lending activity. Second, lenders who supply funds to rural small businesses for re-lending may need to revise their models for credit evaluation if re-lending returns diverge from the rural small businesses' core business activity. Finally, evaluations of financial intermediation in rural areas need to consider the important role of firm-to-firm lending. Perceived capital rationing may not account for trade credit.

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The Pricing of Degree-Day Weather Options

Calum G. Turvey

Abstract

This paper presents a model and framework for pricing degree-day weather derivatives when the weather variable is a non-traded asset. Using daily weather data from 1840–1996, it is shown that a degree-day weather index exhibits stable volatility and satisfies the random walk hypothesis. The options prices from the recommended model are compared to a typical insurance-type model. The results show that the insurance model overprices the option value at-the-money, and this may explain why the bid-ask spread in the weather derivatives market is sometimes very large.

Key words: degree-day options, weather derivatives, weather risk

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The emerging market for weather derivatives has opened new empirical and theoretical challenges for financial economists. A 2004 weather derivatives survey by *Energy Risk* magazine (Lyon) found that the notional value of the market was in excess of $4.6 billion between April 2003 and March 2004. Through June of 2004, more than 25,000 weather contracts, exceeding $580 million, traded at the Chicago Mercantile Exchange (CME), representing a 170% increase over the same period in 2003. Furthermore, the survey indicated that the rise in exchange-traded contracts counters a 20% drop in over-the-counter (OTC) markets. The major sectors using weather derivatives were energy (58.6%), construction (14.4%), and agriculture (8.7%). About 87% of all weather trades involved temperature products, with 7.3% involving rain (Lyon, 2004).

There is a growing interest in using weather insurance or derivatives to manage weather-related risks in agriculture. Some early research included drought insurance pricing or demand with outcomes largely tied to crop yields (Bardsley, Abey, and Davenport, 1984; Patrick, 1988; Quiggen, 1986; Sakurai and Reardon, 1997).

Turvey (2001) identified a number of heat and rainfall products and illustrated how premiums could be calculated using historical probabilities. His study was among the first to posit the notion that the weather itself be insured and that risk management can be obtained without measuring loss. Rather, by identifying specific-event weather risks that correlate with crop yield losses in probability, weather insurance indemnities can be paid out without having to prove yield loss.

Martin, Barnett, and Coble (2001) also developed an actuarial model for computing precipitation insurance for agricultural crops, and Richards, Manfredo, and Sanders (2004) examined pricing issues related to heat-based derivatives associated with fruit crop production in California. Mafoua and Turvey (2003) assessed the feasibility of providing rainfall insurance to protect against rising costs of irrigation in drought years.

To a limited extent, crop insurers and other interests are considering or have implemented weather-based insurance policies for agriculture. Kielmas (2003) reports that the National Australian Bank wrote its first precipitation option in 2003, allowing a payment if September rainfall fell below 21.19 mm. Agricorp, the crop insurer for Ontario, now offers products to protect forage against winter kill and weather-related perils (Turvey, 2001; Kielmas, 2003).

Lacoursiere (2002) reports on a $48 million precipitation put designed for Agriculture Financial Services Corp., the crop insurer for Alberta, in order to insure against a lack of adequate pastureland on which to graze cattle (the precipitation/pasture correlation was obtained from viewing historical satellite images). The puts paid out if precipitation fell below 75% of historical levels between May and July, with a $3/acre cap. Interest is also being shown in weather insurance by agencies such as the World Bank to protect against weather-related risks (Hess, Richter, and Stoppa, ND; Stoppa and Hess, 2003; Skees et al., 2001, 2002; Hazell, Oram, and Chaherli, 2001; Gautman, Hazell, and Alderman, 1994).

Among the greatest challenges are understanding the underlying stochastics of weather variables and how such risks should be priced in the market (Zeng, 2000). The current state of economic analysis is one of disparate opinions with little convergence in ideas. In fact, from a review of the current literature, it appears the only point of agreement is that any model of weather derivatives must consider the market price of risk—but even so, there is little consensus on how this should be accomplished. Furthermore, while there may be agreement on whether the market price of risk should be considered in a model, there are mixed views on whether its value should or should not be zero.[1]

This paper reviews the current literature on the issue as it relates to the class of temperature-based products called degree-day derivatives. These derivative products are based upon such notions as cooling degree-days above 65°F (an indication of electricity demand for air conditioning), heating degree-days below 65°F (an indication of electricity, oil, and gas demand required for heating), and growing degree-days or crop heat units above 50°F (an indication of maximum crop yield potential in agriculture).[2]

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[1] A growing debate raises the question: Is weather insurance an insurance product or a derivative product? In a 2003 white paper by the National Association of Insurance Commissioners, it was argued that weather derivatives are indistinguishable from insurance products (i.e., "weather derivatives are simply weather insurance masquerading as something else"), and should be governed by insurance law which has greater regulatory and oversight policies. In a memo dated January 23, 2004, issued by the Weather Risk Management Association, it was countered that derivatives are distinguished from insurance products on two counts. First, for a product to be classified as insurance, the insured must have an economic interest in the subject matter of the contract; and second, the insured must suffer a pecuniary loss in relation to the insurable interest. As an example, a cattle farmer cannot buy crop insurance if he grows no crops, but can purchase (as a speculator) a futures contract or option on a crop commodity not grown. In addition, a weather product may provide payment when there was no actual loss in the economic interest, or may not pay at all when in fact there was an actual loss in the pecuniary interest. In other words, the possible independence between a risk management product and the economic interest is significant enough to separate a derivative product from an insurance product. This distinction has implications for reinsurance. Reinsurance can only be applied to an insurance product. It cannot be applied to a derivative product.

[2] These contracts are described as cooling degree-day call (put) spreads or heating degree-day call (put) spreads. The options contract (or ticket) has several sections including a general description of the product and the insured event; the specific weather location; the weather units being measured (e.g.,

First, this study addresses how various economic models have been built around historical weather variables; second, the various arguments regarding the market price of risk are reviewed; third, an overview is provided of the variety of pricing models posed in the literature; and fourth, a model is proposed for pricing weather derivatives.

This fourth objective expresses the ultimate goal of this paper. At one level, the analysis is consistent with much of the literature in terms of isolating the deterministic seasonal component of weather, but it differs in how risk is measured. This study develops the dynamic path of cooling/heating/growing degree-days for Toronto over the period 1840 to 1996. Relative to this path, the intra-year volatility of a degree-day index is measured. The stochastics are then tested using a variance ratio test to determine whether the degree-day index (not temperature) follows a random walk (Brownian motion). The results fail to reject the Brownian motion null. This result unto itself is significant because it implies that standard models—i.e., equilibrium counterparts to Black and Scholes (1973)—can be used to price weather derivatives, despite the fact that the majority of authors reject the notion of Brownian motion outright and without formal testing. However, as is pointed out, the rejection is based upon path dependence in the weather outcome, and not the forward value of a degree-day index. The distinction is not trivial.

This paper also discusses the market price of risk, which is another contentious issue in pricing weather derivatives. Here, I present what appears to be a minority view that the market price of risk should, in equilibrium, be zero. I base this argument on capital market equilibrium. In short, while it is recognized that there are unhedgable risks associated with non-traded assets which could give rise to a market price of risk in equilibrium, the risks associated with localized weather patterns (e.g., Toronto) will be technically uncorrelated with the market portfolio. In other words, the risks associated with degree-day weather derivatives are comprised wholly of diversifiable risk.

Estimating Stochastic Paths

One of the problems facing the weather derivatives markets is how these derivatives should be priced. In the absence of a tradable contract in weather, an equilibrium price cannot be established using conventional means (Dischel, 1998). At one end of the pricing spectrum, Cao and Wei (1999, 2004) develop a pricing model based on expected utility maximization with an equilibrium developed from Lucas' (1978) model, a framework repeated by Richards, Manfredo, and Sanders (2004). Davis (2001) also concludes that a Black-Scholes type framework is not appropriate for pricing weather derivatives as a matter of course; but, under the assumptions of Brownian motion, expected utility maximization, a drift rate that includes the natural growth rate of the degree-day measure, the natural growth rate in the spot price of a commodity (e.g., fuel price), and the natural growth rate in firm profits, then degree-day options can be priced by a Black-Scholes analogue. Leggio and Lien (2002) employ a model developed by McIntyre (1999) to estimate calls on heating degree-day (HDD) traded futures contracts while using Black-Scholes to calculate puts. Considine (ND) provides

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degree-days or rainfall); the weather index being used (e.g., cooling, heating, or growing degree-days for the contract term); the contract term (e.g., June 1 to August 31); the index strike (e.g., 400 cooling degree-days); the unit price and currency (e.g., $5,000 per cooling degree-day); the settlement terms which indicate the specific source of weather information, the timing for payment, and any adjustments made due to revisions from the weather authority; and the buyer's premium. Likewise, the CME has specified CDD and HDD futures contracts for each month of the year for 20 cities across the USA. Thinly traded, the futures contracts are based on cumulative degree-days within the month, and settlement is based on readings supplied by Earth Satellite Corporation. The notional value of the futures contract is equal to $100 times the CDD or HDD index value. CME degree-day options on CDD and HDD futures are listed in units of degrees Fahrenheit.

some simpler formulas based on the historical probability distribution of weather outcomes as well as a Gaussian (normality) model that he claims can be sufficient at times.

The predominant approach to pricing weather derivatives is to first develop an econometric model to forecast the path of temperatures and then to use the forecasting model to measure degree-day risk. Richards, Manfredo, and Sanders (2004) use a model of the form:

$$(1)\quad dw_t = k(\alpha_w(w_t, t) - \lambda\phi - w_t)dt + h_t(w_t, t)dz + \phi dq,$$

which describes a mean-reverting (at rate k) Brownian motion with drift μ, lognormal jumps (arriving at rate λ with shock ϕ from the Poisson process q), and time-varying volatility $h(\cdot)$ against a Wiener process, dz.

To obtain the parameters for equation (1), Richards, Manfredo, and Sanders estimate the autoregressive process

$$(2)\quad \alpha_w(w_t, t) = \gamma_0 + \gamma_1 \sin\left(\frac{2\pi t}{365}\right) + \gamma_2 \cos\left(\frac{2\pi t}{365}\right) + \gamma_3 t + \sum_{j=1}^{p} \rho_j w_{t-j}$$

with an ARCH process:

$$(3)\quad h_t(w_t, t) = \gamma_0 + \gamma_1 (w_{t-1} - \alpha_w)^2.$$

The model includes seasonality as defined by the sin(·) and cos(·) functions, and trend as captured by γ_3. This is similar to the models of Campbell and Diebold (2003), and Alaton, Djehiche, and Stillberger (2002), except that Campbell and Diebold use a GARCH process and a much longer autoregressive process to capture long-memory dynamics [Richards, Manfredo, and Sanders (2004) found that a regressive process of 3 was sufficient], while Alaton, Djehiche, and Stillberger exclude the autoregressive process, i.e.,

$$(4)\quad \alpha_w(w_t, t) = \gamma_0 + \gamma_1 \sin\left(\frac{2\pi t}{365}\right) + \gamma_2 \cos\left(\frac{2\pi t}{365}\right) + \gamma_3 t.$$

The model developed by Cao and Wei (2004) is somewhat different. They define the residual daily temperature as

$$(5)\quad U_t = w_t - \left(\frac{\beta}{365}\left(t - \frac{T}{2}\right) + \bar{w}_t\right),$$

and then model temperature dynamics assuming U follows a k-lag autocorrelation process:

$$(6)\quad U_t = \sum_{t=1}^{k} \rho_t U_{t-1} + \sigma_t \xi_t,$$

$$(7)\quad \sigma_t = \sigma_0 - \sigma_1 \left|\sin\left(\frac{\pi t}{365} + \phi\right)\right|,$$

and

$$(8)\quad \xi_t \sim N(0, 1),$$

where t is the day index, T is the total number of observations available, β captures any global warming, $\bar{w}_t$ represents the daily historical average temperature within the sample, and ϕ is used to capture the proper starting point of the sin wave. In other words, the Cao and Wei model uses a function of the daily deviation from the daily historical mean.

The common element among these papers is that they all estimate the dynamic path of the underlying temperature process rather than the process of a degree-day index. The problem with this approach is that there is no guarantee the underlying drift in temperature will be the same as the drift for a degree-day index. In fact, it should not be. Richards, Manfredo, and Sanders (2004) state that they use the weather variable rather than the degree-day variable to avoid unnecessary complications related to the truncation point, and then use their estimated process to simulate degree-day values. The compromise employed by Alaton, Djehiche, and Stillberger (2002) is to restrict the calculation of degree-days over

a time horizon for which the probability that the cooling degree-day measure, $\text{Max}(65 - w_t, 0) = 0$, is close to zero. Under this assumption, the underlying drift (including mean reversion and jump processes if included) of the degree-day index will be identical to that of the temperature variable.

The usual process for calculating degree-days is given by:

$$(9) \quad HDD_T = \sum_{t=1}^{T} \text{Max}\big(65 - g(w_t, t), 0\big),$$

$$(10) \quad CDD_T = \sum_{t=1}^{T} \text{Max}\big(g(w_t, t) - 65, 0\big),$$

and

$$(11) \quad GDD_T = \sum_{t=1}^{T} \text{Max}\big(g(w_t, t) - W, 0\big)$$

for heating degree-days, cooling degree-days, and growing degree-days, respectively. The function $g(\cdot)$ describes the stochastic process from any start point t to any end date T. The use of 65°F corresponds with standard industry practice as defined by the energy industry.[3] For growing degree-days, the variable W is used to indicate that it need not be fixed at 50°F, but can be any value. Using DD to denote any degree-day measure, an option on the degree-day is given by

$$(12) \quad v_{DD}^{c} = e^{-(\mu-\lambda\sigma)T} E\big[\text{Max}(DD_T - Z_{DD}, 0)\big],$$

$$(13) \quad v_{DD}^{p} = e^{-(\mu-\lambda\sigma)T} E\big[\text{Max}(Z_{DD} - DD_T, 0)\big],$$

for calls and puts, respectively; and $\mu - \lambda\sigma$ is the risk-neutral drift rate (Cox and Ross, 1976), with μ now defined as the natural drift of the degree-day index, and λ now defined as the market price of risk. The normal procedure is to start accumulating degree-days along the path $g(\cdot)$ beginning at $t = 1$ and ending at $t = T$. For example, a growing degree-day will be calculated on each date using $\text{Max}(g(w_t, t) - W, 0)$. The path $g(\cdot)$ can be a deterministic path using historical data for years $n = 1, \ldots, N$, so that

$$(14) \quad E\big[\text{Max}(Z_{DD} - DD_T, 0)\big] = \frac{1}{N} \sum_{n=1}^{N} \sum_{t=1}^{T} \text{Max}(Z_{DD} - DD_{t,n}, 0).$$

This is the burn-rate approach used by insurance companies (Muller and Grandi, 2000; Turvey, 2001). If $g(\cdot)$ is simulated as a stochastic process, then

$$(15) \quad E\big[\text{Max}(Z_{DD} - DD_T, 0)\big] = \frac{1}{K} \sum_{k=1}^{K} \sum_{t=1}^{T} \text{Max}\big(Z_{DD} - \hat{g}_k(w_t, t), 0\big)\, dw_t.$$

In either case, the task is to calculate path dependence from $t \to T$ for each year in the sample and then take the mean of the accumulated degree-days across all years. Here, $\hat{g}_k(w_t, t)$ is a stochastic process, and using Monte Carlo methods the derivative price is obtained over K iterations. This appears to be the generating function used by Richards, Manfredo, and Sanders (2004), and Cao and Wei (2004). A variant on this approach, proposed by Campbell and Diebold (2003), can be generalized as:

$$(16) \quad E\big[\text{Max}(Z_{DD} - DD_T, 0)\big] = \frac{1}{N} \sum_{n=1}^{N} \sum_{t=1}^{T} \text{Max}\Big(Z_{DD} - \int \hat{g}_n(w_t + \varepsilon, t) \times f_t(\varepsilon)\, d\varepsilon, 0\Big).$$

Here, Campbell and Diebold introduce the empirical distribution function $f_t(\varepsilon)$, where ε represents a temperature shock. There are T such distributions, one for each day. For each day (t) in each year (n), the estimated temperature outcome is perturbed by k draws from $f_t(\varepsilon)$. Using Monte Carlo simulations, Campbell and Diebold make 250 random draws for each of 151 days and for each of 41 years.

Rather than using either the burn-rate or Monte Carlo methods, are there approaches that can use closed-form

[3] The term cooling degree comes from the increased use in air-conditioning units when temperatures rise above 65°F, while the term heating degree comes from the increased use of energy for heating when temperatures fall below 65°F.

equilibrium pricing models around the Black-Scholes line? From a purely mathematical point of view, closed-form solutions can be obtained for non-tradable assets if (*a*) the underlying risk follows a geometric Brownian motion, and (*b*) buyers and sellers are adequately compensated for non-tradable risk. The assumption of Brownian motion has been largely disregarded as being naïve, since weather patterns tend to be autocorrelated, mean-reverting, and with seasonal trends. However, the problem with pricing degree-day derivatives is not that the underlying weather variables follow a Brownian motion, but that on expectation, the degree-day index being insured follows a Brownian motion. This argument has not previously been treated as a hypothesis, and therefore has not been tested.

To satisfy the Brownian motion, the stochastic process governing cumulative degree-days must have:

$$(17)\quad \mu_t = \ln\left(\frac{W_t^*}{W_{t-1}^*}\right)$$

and

$$(18)\quad \sigma = \sqrt{E[\mu - \bar{\mu}]^2},$$

where W^* is the expected value of the degree-day index on day $t \leq T$, μ is the daily drift, and σ is the daily volatility. It is assumed W^* evolves dynamically as

$$(19)\quad dW_t^* = \mu W_t^* + \sigma W_t^* dZ$$

in its natural state, but in its traded state it follows

$$(20)\quad dW_t^* = (\mu - \lambda\sigma)W_t^* + \sigma W_t^* dZ,$$

which adjusts for the market price of risk (λ). Defining the opportunity cost of capital as the risk-free rate, the equilibrium call option value (Constantinides, 1978; MacDonald and Siegel, 1984) with strike price X is:

$$(21)\quad V_{call} = W_0^* e^{(\mu-\lambda\sigma-r)T} N(d1) - Xe^{-rT} N(d2),$$

where

$$(22)\quad d1 = \frac{\ln\left(\frac{W_0^*}{X}\right) + (\mu - \lambda\sigma + \tfrac{1}{2}\sigma^2)T}{\sigma\sqrt{T}}$$

and

$$(23)\quad d2 = \frac{\ln\left(\frac{W_0^*}{X}\right) + (\mu - \lambda\sigma - \tfrac{1}{2}\sigma^2)T}{\sigma\sqrt{T}}.$$

The equivalent put value is:

$$(24)\quad V_{put} = Xe^{-rT} N(-d2) - W_0^* e^{(\mu-\lambda\sigma-r)T} N(-d1).$$

If W^* is a traded index, such as the degree-day futures contracts traded on the CME, then even in the absence of a hedgable economic interest, the risk-neutral drift rate can be applied such that

$$(25)\quad \lambda = \frac{\mu - r}{\sigma}.$$

Substituting for the risk-neutral drift rate, the equilibrium model becomes Black-Scholes equivalent. If the weather index is a traded futures contract, then substituting $W_0^* = e^{-rT} W_T^*$ for W_0^* results in Black's (1976) model. However, this also assumes W^* is pecuniary in nature. In reality, $W_0^* = W_T^*$, and thus the initial index value is the expected expiration value.

The more general form of equations (21) and (24), in which it is assumed throughout that the underlying degree-day index is not traded, may be preferable. In the absence of a market it is not feasible to impute risk neutrality, and therefore the drift rate and market price of risk remain as part of the solution. Since $W_0^* = W_T^*$, the natural expectation is that there is zero drift, or instantaneous mean reversion.

The market price of risk is more problematic. Its definition is ubiquitous and its measurement is difficult. In the most general sense, we can define

$$(26)\quad \hat{r} = r + \lambda\sigma,$$

which states that the rate of return from an investment is equal to a risk premium

($\lambda\sigma$) above the risk-free rate to compensate the investor for unhedgable risks. Leggio and Lien (2002) use a model developed by McIntyre (1999) to estimate puts and calls on HDD traded futures contracts while using Black-Scholes to calculate puts. Although they recognize the need to account for non-tradability, they make no adjustments to their model.

Alaton, Djehiche, and Stillberger (2002) ultimately assume a model based on the Martingale restriction. By assuming the Q measure, they implicitly assume an arbitrage-free equilibrium under the risk-neutral measure. To do so, they calculate the HDD call option price assuming $\lambda = 0$, and compare this to observed (OTC) contract prices. They then infer the market price of risk which most closely matches actual prices, observing that despite similar risks in the underlying, market prices of risk differ across contracts.

Cao and Wei (2004), and Richards, Manfredo, and Sanders (2004) apply the Lucas (1978) general equilibrium valuation model to capture the market price of risk. Productivity in the economy is represented by equity claims, and these equity claims depend on weather according to an autoregressive model. To measure this, Cao and Wei (2004) use gross national product (GNP) and aggregate consumption for five U.S. cities to estimate the relationship between the aggregate dividend and weather. They report that the correlation is low and switches between positive and negative depending on the season. Across all cities, the average correlation over all months was only -0.0739, but was -0.188 for HDD months and 0.338 for CDD months. Using aggregate annual consumption data for Fresno County in California, Richards, Manfredo, and Sanders (2004) find that there exists a relationship between consumption and weather. They therefore conclude the market price of risk is not zero.

Others argue the market price of risk is zero. Froot and Posner (2001) discuss this in relation to catastrophe bonds. The essence of their argument is that the market price of risk will be zero if there is no correlation between the event derivative and the event itself. They note investors in such instruments receive premiums which appear to be higher than actuarial rates, in some cases explained by parameter uncertainty. While Froot and Posner show that ambiguity about parameters in a model may give rise to positive market prices of risk, they also conclude that in the absence of parameter uncertainty the market price of risk will be zero if the investor has no prior holdings of the event risk, and event risk is independent of other financial assets. This implies that even within the context of the Sharpe-Lintner Capital Asset Pricing Model (CAPM), the underlying risk will be zero beta if the weather event is uncorrelated with the market portfolio.

The use of CAPM to make this argument is not unreasonable if we wish to assume equilibrium. If weather risk is significantly correlated with productivity in one region of the economy [e.g., Fresno County as found by Richards, Manfredo, and Sanders (2004)], an investor can diversify this risk by investing in other regions with uncorrelated weather patterns, and hence uncorrelated risk. In other words, would the correlations reported by Richards, Manfredo, and Sanders (2004), and Cao and Wei (2004) between weather and the dividend yield for particular cities or counties be compensated by a market in which these risks can be diversified via spatial investment? Moreover, there is an overriding asymmetry in the correlations between consumption, investment, and weather. There may be a causal relationship between the weather risks in a specific locale and the market portfolio, but it is impossible to conclude there is a causal relationship between changes in the market portfolio and the weather. Specifically, while market forces work toward equilibrium in an economy through transparent price discovery, nature is under no obligation to comply with subjective market assessments.

Accordingly, the pricing is assumed to be zero beta in the CAPM equilibrium sense, which requires that the market price of risk, λ, be zero.[4] This is not to discount the findings of Cao and Wei (2004), and Richards, Manfredo, and Sanders (2004), who show a positive correlation between weather and the aggregate dividend yield. Rather, their results are recognized here to reflect local correlations that are idiosyncratic and diversifiable in a global context.

Defining a Weather Index

In this section, a general approach to constructing a weather index using historical data is presented. In the next section, the index model is applied to a case study of degree-day contracts for Toronto. To construct such an index, it is useful to draw on a unique characteristic—the weather index cannot be influenced by human speculation. In this context, the index is observable, objective, and representatively transparent. For example, settlement of the CME contracts is based exclusively on the data collected by Earth Satellite Corporation.

Furthermore, a consistent characteristic of weather is that it is seasonal and systematic—e.g., summer always starts off with low temperatures that rise to a peak, and then decrease toward autumn. A naïve hedger planning a hedge in early spring would naturally assume the summer weather pattern would follow the average pattern as dictated by history. Critical to this hypothesis is the additional assumption that temperature is mean-reverting: In the absence of any contrary information, it is not unreasonable to assume that if the average temperature on June 30th is 70°F, then in the current year the best unbiased estimate is that it will also be 70°. The notion of mean reversion is also a natural phenomenon; the tendencies for temperature to fall to within a normal range following a heat wave, or to rise to normal temperatures following a cold snap, are clearly the norm rather than the exception.

The absence of predictability and the assumption of mean reversion suggest that the best initial ($t = 0$) unbiased estimate of the forward index is the historical average of the index over the specified contract time horizon. Indeed, the opening trade on the CME futures contracts will most likely be the long-run average cumulative degree-day with some adjustment for long-term forecasts or revised expectations. The initial index value is given by equation (27):

$$(27) \quad W_0^* = E[W_T] = \sum_{t=1}^{T} E[W_t],$$

where W represents the weather index (e.g., cooling degree-days, heating degree-days, growing degree-days). After one day, the observed weather condition at $t = 0$ is recorded, and the index value is appropriately adjusted to include the actual outcome plus the projected outcome:

$$(28) \quad W_1^* = W_1 + \sum_{t=2}^{T} E[W_t].$$

Similarly, at $t = 2$,

$$(29) \quad W_2^* = W_1 + W_2 + \sum_{t=3}^{T} E[W_t],$$

and for any time increment k in the sequence,

$$(30) \quad W_k^* = \sum_{t=1}^{k} W_t + \sum_{t=k+1}^{T} E[W_t].$$

As the index evolves with time, the instantaneous percentage change in the weather index can be calculated as

$$(31) \quad E[\mu] = E\left[\frac{\left(W_k^* - W_{k-1}^*\right)}{W_{k-1}^*}\right],$$

and daily volatility is specified as

$$(32) \quad \sigma^2 = E\left[\mu - E[\mu]\right]^2.$$

[4] In other words, $\lambda = \beta[r_m - r]/\sigma$, where β is the degree-day beta that measures the covariance between the degree-day measure and the return on the market portfolio, r_m.

Finally, under the assumption of mean reversion, the path described by

$$\sum_{t=1}^{T} E[W_t]$$

must be estimated. This can be done by using historical data directly, but since this measure must be recalculated for each day in the contract's life, it is computationally intense. In the alternative,

$$\sum_{t=1}^{T} E[W_t]$$

can be estimated from a simple regression equation to obtain the same result. In this study, the estimated equation describing the evolution of degree-days during the summer months was quadratic.

The Pricing of Cooling Degree-Day Options

In this section, option premia are calculated for Toronto, Ontario, using Environment Canada daily mean temperatures from 1840 to 1996. The contracts examine summer cooling degree-day call (put) spreads. With this option the buyer agrees to pay a fixed premium in exchange for payment from the seller if the defined weather index settles above (below) the index strike for the contract term. The payment equals the number of weather units the weather index falls above (below) the index strike times the unit price. There may be a payout limit, but this is not considered here.

- First, the temperature history from June 1 through August 31 is described from a historical perspective. As history will always be the source of weather patterns, it is important to understand how more recent trends compare to past trends.

- Second, using a cooling degree-day measure of heat above 65°F, degree-days are calculated for each day, and cumulative degree-days are calculated for each year.

- Third, a quadratic regression equation is estimated with mean daily degree-days as the dependent variable, and time and time squared (within the contract term) as the independent variables. The equation used in the examples provided in this paper is given by

$$(33) \quad E[W_t] = -0.38 + 0.21t - 0.002t^2,$$

and its integral is written as

$$(34) \quad \int_t^T E[W_t]\,dt = -0.38t + 0.105t^2 - 0.00067t^3.$$

The pattern is parabolic, and the statistical fit (using a quadratic equation) of predicted to average was approximately 93% (R^2), with only the intercept not being statistically different from zero. One might compare this with the paths defined by equations (2) and (4), which measure seasonality via a sin function. Since the sin functions simply represent sequences of quadratic and cubic functions, measuring historical wave patterns is not essential. The difference is that in estimating sine functions all historical data are used in sequence, and then the function is used to estimate weather patterns between t_1 and T. Our approach is to first collect all of the data from t_1 to T, and then to estimate the time function in (33).[5]

- Fourth, using mean cumulative cooling degree-days as the initial index value, observed daily degree-days (W_t), and the regression equation (33), the forward index value for each day in each year (W_k^*) was calculated according to

$$(35) \quad W_k^* = \sum_{t=1}^{k} W_t + \int_{k+1}^{T} E[W_t]dt.$$

In other words, the index value on day $k \geq 1$ in real time is given by the sum of actual degree-days from $t = 1$ to k, and the sum of the expected degree-days from day $k + 1$

[5] From a computational point of view, patterns over cold months will be quadratic and convex, over warm months quadratic and concave [as in equation (33)], and between seasons, cubic.

to T. The sum of the expected degree-days is given by the integral of the quadratic equation [i.e., equation (34)]. Here the point of reviewing previous models [see equations (2) through (8)] becomes evident. In those earlier studies, an autoregressive process was used in order to provide a temperature prediction equation which was then used in simulation to estimate put and call premiums. In the current study, historical degree-days were first calculated and then fitted to a seasonality function. This function provides the expected value of a degree-day on any particular day.

- Fifth, using the daily forward index values, the empirical volatility of the index is calculated from the variance of the daily percentage change in index values. This is done for each year.

- Sixth, assuming a discount rate of 6.5%, the historical mean volatility, 92 days to expiration, and a strike price (which is varied), call and put option premiums are calculated. As a point of comparison, premiums using the "burn-rate," or historical data, approach are also calculated.

Toronto's Weather History

This section describes the weather history from June 1 to August 31 for the years 1840–1996 in Toronto. The data (plotted in Figure 1) were obtained from Environment Canada, and represent one of the longest available weather data series in Canada. The plot shows an overall increase in mean daily temperature over this time period, with temperatures increasing at an increasing rate until approximately 1930, and then increasing at a decreasing rate. Since approximately 1950, there does not appear to be a significant rise in mean daily temperatures.

Figure 2 shows the cumulative cooling degree-days in Toronto between 1840 and 1996. The cooling degree-days increase with the mean temperature as would be expected, but the graph also illustrates the variability and unpredictability of the measure. Cooling degree-days increased at an increasing rate throughout most of the 19th century, but appear to be quite stable or decreasing in terms of mean value toward the end of the 20th century.

Table 1. Historical Summary of Toronto Cooling Degree-Days

Period	Mean	Std. Dev.	Min.	Max.
1840–1996	379.39	146.67	107.10	787.02
1930–1996	489.50	114.69	186.12	787.02

Table 1 summarizes the key statistics for the entire 1840–1996 period and the subperiod of 1930–1996. Over the 1840–1996 period, the average cooling degree-days ranged from 107 to 787, with a mean of 379 and a standard deviation of 147. The 1930–1996 subperiod has cooling degree-days ranging from 186 to 787, with a higher mean of 489 and a standard deviation of 114.

Figure 3 illustrates the mean and predicted daily degree-days within the 92-day period from June 1 to August 31. Figure 4 illustrates the cumulative degree-day effect throughout the same time period. The degree-day value used for options pricing is the total sum recorded on the 92nd day.

Calculating the Cooling Degree-Day Weather Index

This section describes how the CDD weather index was calculated. The index was calculated for each year in order to assess the range of CDDs and to measure volatility. The cooling degree-day weather index was generated from a combination of observed daily data in each year, the seasonal regression equation, and the average cumulative degree-day value across all years. The initial index value at $t = 0$ is assumed equal to the average cumulative degree-day value. This is identical to the sum of the marginal degree-days illustrated in Figure 3.

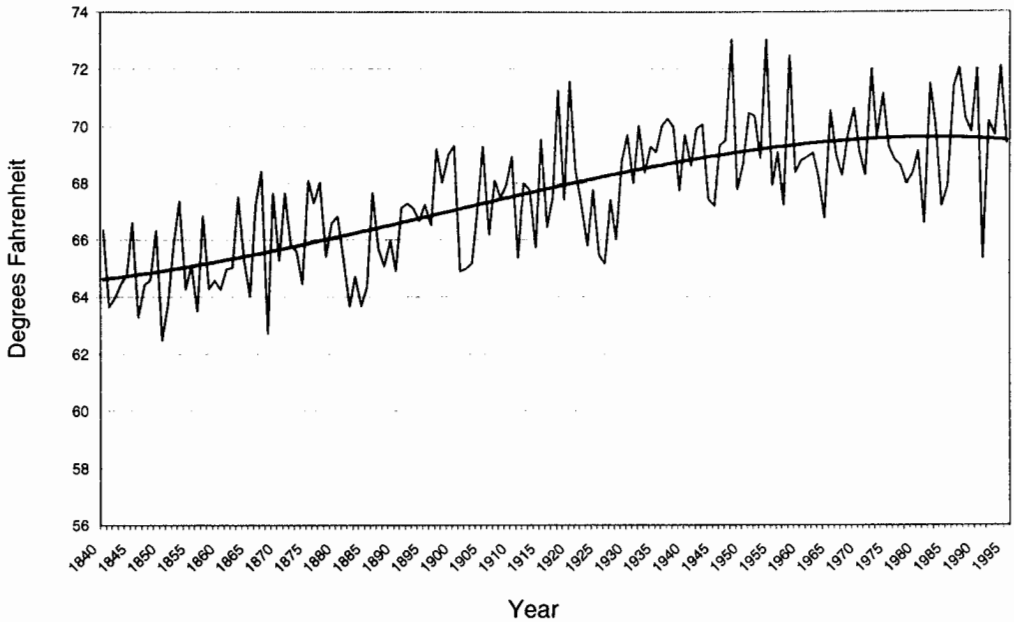

Figure 1. Mean Seasonal Temperature, Toronto, June 1 to August 31 (1840–1996)

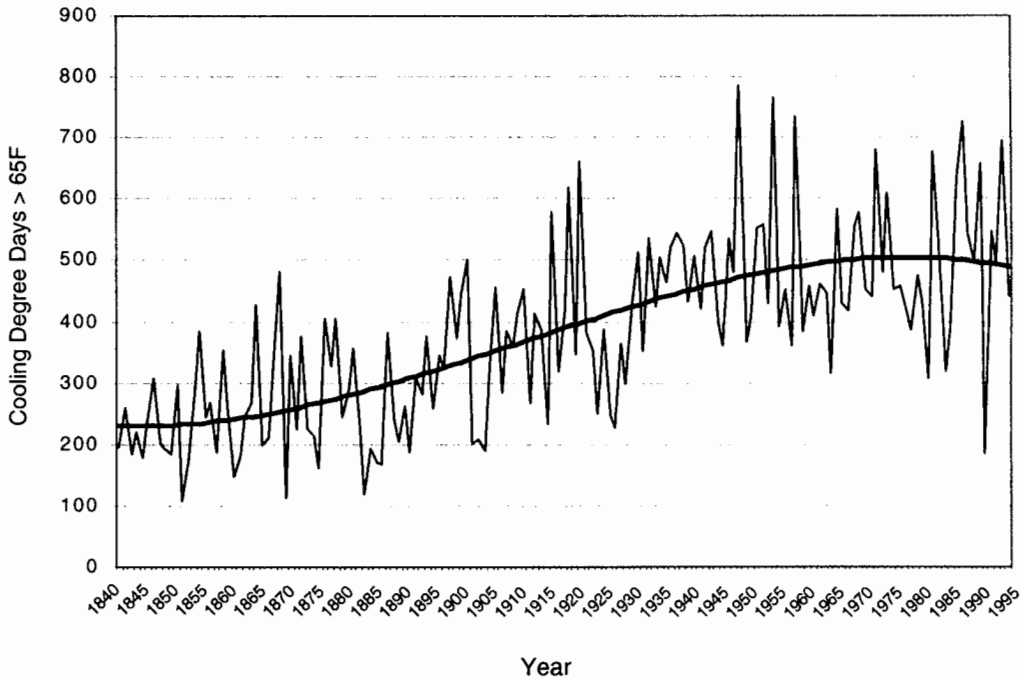

Figure 2. Mean Actual and Predicted Daily Cooling Degree-Days, Toronto, June 1 to August 31 (1840–1996)

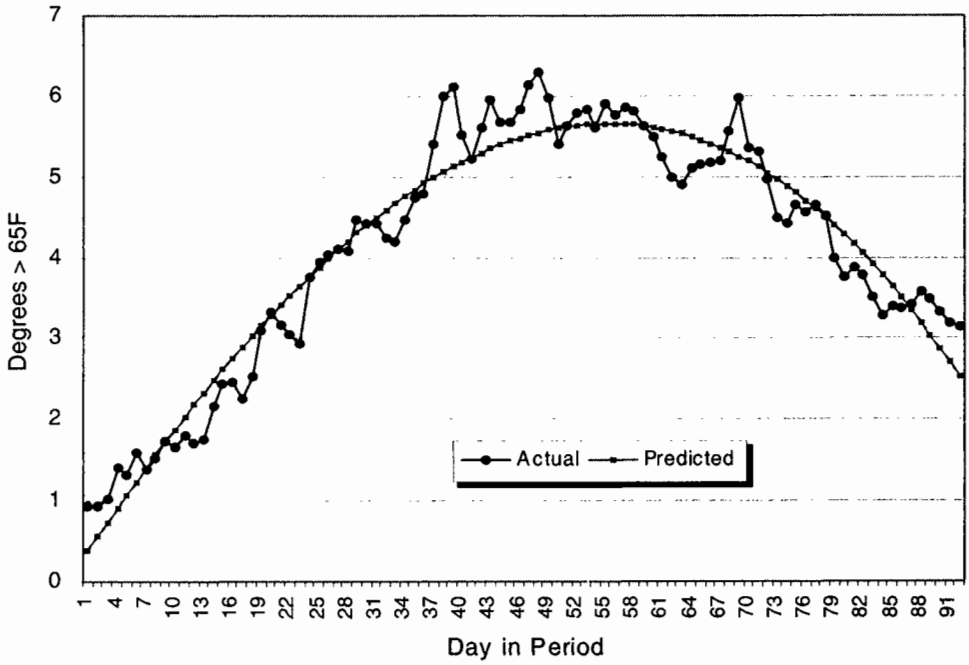

Figure 3. Mean Daily Cooling Degree-Days, Actual and Predicted, Toronto, June 1 to August 31

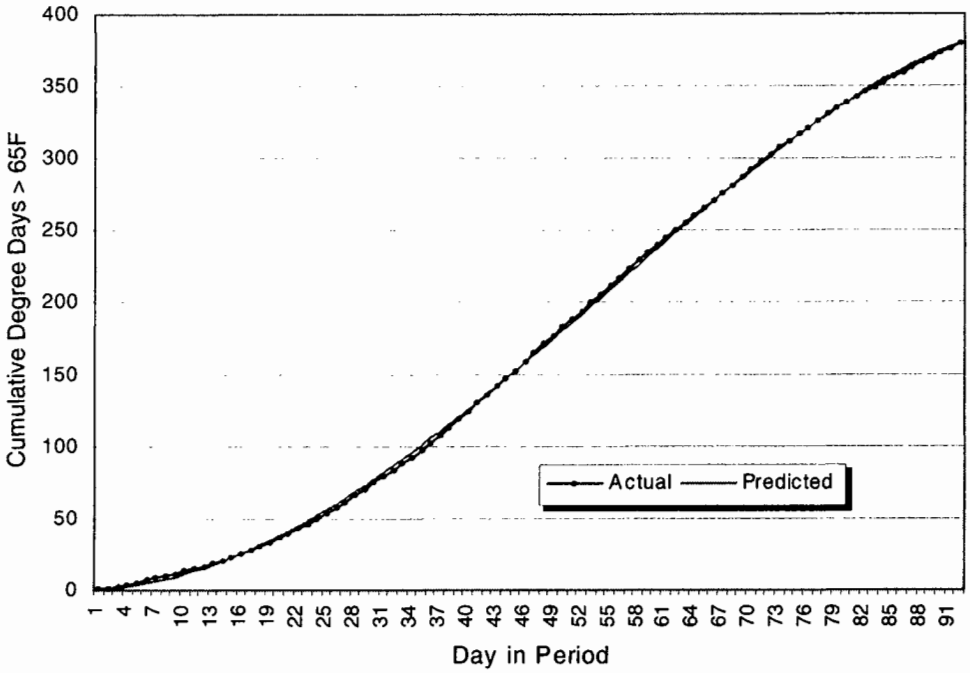

Figure 4. Cumulative Cooling Degree-Days, Actual and Predicted, Toronto, June 1 to August 31

Table 2. Historical Summary of Toronto Cooling Degree-Days' Volatility

Period	Mean	Std. Dev.	Min.	Max.
1840–1996	0.2063	0.0012	0.1662	0.2961
1930–1996	0.1739	0.0009	0.1414	0.2350

The smooth parabola in Figure 3 illustrates how the regression equation smoothes the variability in daily degree-day measures and acts as an unbiased predictor of the most likely temperature path based on the assumption that weather patterns are mean-reverting.

To calculate the index, the degree-day above 65°F is calculated from the first observation (day 1). Then the sum of the predicted daily degree-days is calculated along the parabola from day 2 through day 92. Assuming that the day 1 degree-day measure is small, this will provide a day 1 index value very close to the long-run average. On day 2, the actual degree-day measure is taken and is added to the day 1 value. The sum of the predicted daily degree-days is then taken from day 3 to day 92 and added to the actual day 1 plus day 2 values [see equation (35)]. This procedure is repeated for each of the 92 days within the year and is repeated for each year in the sample.

Figure 5 illustrates the results for three recent years in Toronto (1986, 1988, and 1992). In 1986, which was an average year with cooling degree-days of 386, the summer started off quite cool, and this caused the index to fall below the average until about day 55 where a warming trend caused a slight increase in the value of the index. In 1988, a hot year, the index was above average throughout the season. A short cooling spell from day 31 to about day 40 caused the index to decrease, but beyond that cooling degree-days were significantly higher than average. The 1988 index peaked at approximately 750 on day 80, but a cooling trend caused the index to fall to 725 by day 92. Finally, in contrast to 1986 and 1988, 1992 was unusually cool, with cumulative degree-days of 186 by day 92. The index was average for the first three weeks of June, but then a long cooling trend caused the index to fall to a low of about 180 before ending at 186.

Calculating Volatility

Volatility is measured relative to the percentage change in the value of the index on a daily basis, and then converted to an annualized (365-day) basis for convenience. Table 2 reports the estimated average volatility for Toronto cooling degree-days over the 1840–1996 period and for the 1930–1996 subperiod. These data are plotted graphically in Figure 6.

The results indicate that the weather has actually been less variable since 1930 than in the previous 90 years. From 1840 to 1996, annualized volatility was 0.2063 or 20% per year, but this decreased to 0.1739 or 17% per year in the mid- to latter part of the 20th century. For the entire period, the minimum volatility was found to be 16.62% with a maximum of 29.61%, while in the latter part of the century the range was as low as 14.14% but only went as high as 23.5% (Table 2).

Combined with the information in Table 1, weather averages in Toronto saw an increase in mean summer temperatures and degree-days, but this increase did not come with increased variability. In fact, the standard deviation of cumulative degree-days (Table 1) is lower for the 1930–1996 period than for the 1840–1996 period. Importantly, these observations signify that when options on weather are being priced it is necessary to match recent weather trends on index values and volatility. In the next section, which calculates option premia, an approach to mitigate this problem is discussed.

Volatility Stability

Use of the options pricing model requires stability in the index's volatility within a given year and across years. The first item is important because if daily volatility is a

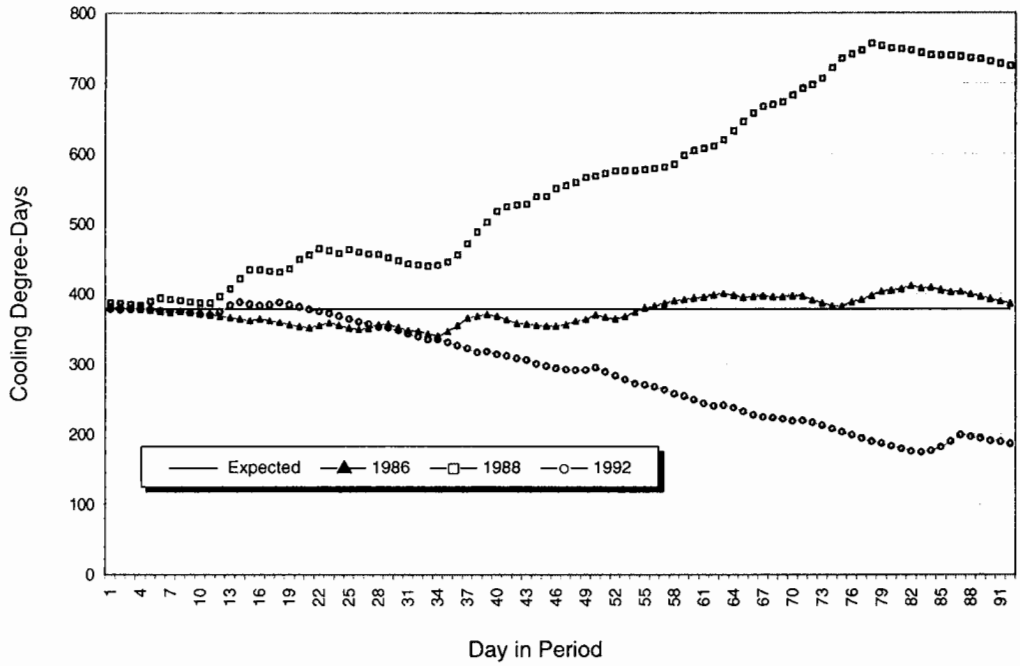

Figure 5. Cooling Degree-Day Weather Index for 1986 (average), 1988 (above average), and 1992 (below average), Toronto, June 1 to August 31

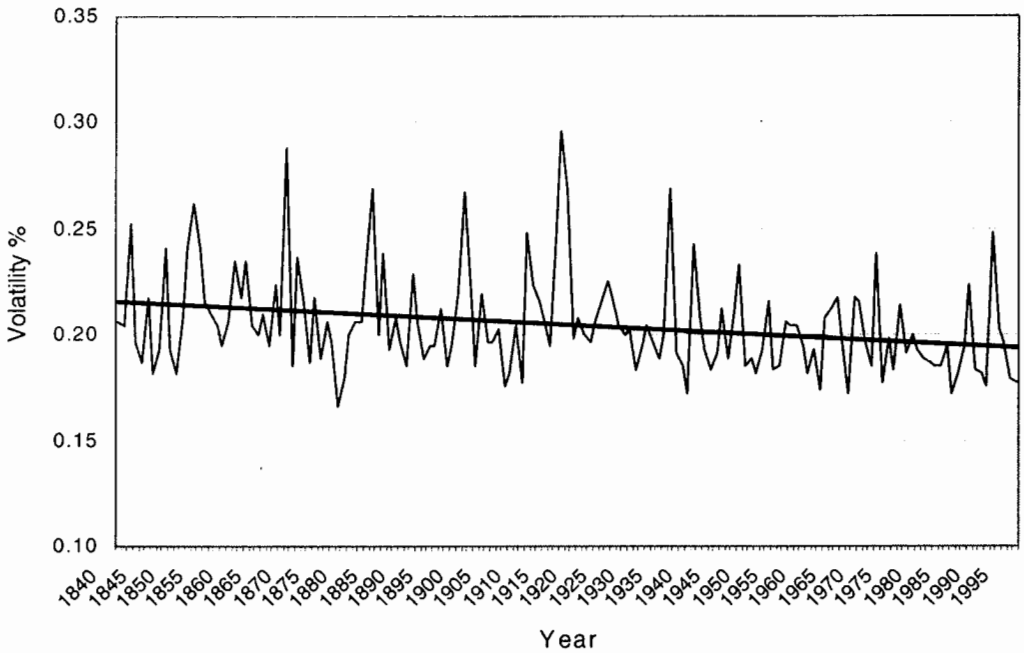

Figure 6. Mean Annualized (365-day) Volatility, Toronto Cooling-Degree Days, June 1 to August 31 (1840–1996)

Table 3. Estimation Results for Seasonality and Stability in Volatility

Description	1840 to 1996	1840 to 1935	1936 to 1996
Mean (365 days)	0.201	0.207	0.193
Standard Deviation	0.023	0.022	0.021
Coefficient of Variation Mean	6.420	5.980	7.130
Coefficient of Variation Standard Deviation	3.190	3.030	3.320

function of time or is characterized by discernable jumps, the proposed pricing model will be misspecified. The second is important because stability in volatility across years means that the sample volatility can be used as an unbiased estimate of volatility.

Volatility stability was measured by calculating the percentage daily change in the weather index in each year (91 days), i.e., $\ln[W_T/W_{t-1}]$. To determine the stability of volatility, rolling 30-day standard deviations of the percentage change were calculated and annualized to a 365-day year. Thus, for the 91 days used in this study, there were 61 volatility estimates for each year. Table 3 shows the results from this evaluation over the 1840–1996 period and for two subperiods, 1840–1935 and 1936–1996.

The annualized volatilities have been stable across years, with the average 30-day volatility being about 20%. This compares to the average volatility over the entire 91 days of 0.2063 as shown in Table 2. The results also show that the standard deviations are low relative to the mean. For example, a standard deviation of 0.023 for 1840–1996 indicates that the average 30-day volatilities ranged from 0.178 to 0.223 approximately 67% of the time. The within-year coefficient of variation (mean/standard deviation) reveals that the means are 6.42, 5.98, and 7.13 times the within-year 30-day standard deviations for each of the respective periods. As implied by these numbers, not only is volatility stable across years, but it is quite stable within each year as well.

The Variance Ratio Test for Random Walks

The pricing of weather derivatives using equations (21) or (24) requires that the weather index (W_T^*) evolves over time as a random walk described by geometric Brownian motion. In addition, the model assumes the volatility of W_T^* is fairly stable. Failure to show stability in volatility would require expanding the model to include a volatility diffusion or jump process as done by Richards, Manfredo, and Sanders (2004).

A general test for a random walk, as presented by Lo and McKinley (1999), is the variance ratio test. Under the normal definition of a diffusion process, the expectations are that the mean diffusion rate is constant and volatility is linear in time. Hence, the mean return on an asset with two time steps will be twice that for a single time step, and likewise the variance of the two time steps will be double that of a single time step. These conditions can be stated as follows:[6]

(36a) $E[W_{t+1} - W_t] = \mu_1$,

(36b) $E[W_{t+k} - W_t] = k\mu_1$,

(36c) $\mathrm{Var}[W_{t+1} - W_t] = \sigma_1^2$,

(36d) $\mathrm{Var}[W_{t+k} - W_t] = k\sigma_1^2 = \sigma_k^2$,

where k represents the number of time steps, μ_k represents the mean of a k-step (or k-day) diffusion, and σ_k^2 represents the variance of a k-step diffusion. This property allows for a simple test of the random walk by testing the null hypothesis:

$$H_0: \frac{\sigma_k^2}{k\sigma_1^2} - 1 = 0.$$

[6] If levels data are used, the conditions apply to arithmetic Brownian motion; if $\ln(W_t)$ is used, they apply to geometric Brownian motion. The tests in this paper use the logarithmic conversion, but the notation of W_t is not changed.

Lo and McKinley (1999) provide a measure of the asymptotic variance for the variance ratio. If

$$(37)\quad Z = \frac{\sigma_k^2}{k\sigma_1^2} - 1,$$

then

$$(38)\quad \sigma_z^2 = \frac{2(2k-1)(k-1)}{3(N-1)k}$$

is the asymptotic variance of z when overlapping lags of length k are drawn from N observations. Thus the null hypothesis can be tested against the standardized normal z-test with mean and variance σ_z^2. For example, if $z < 1.96$ in equation (37), we would fail to reject the null hypothesis at the 5% level if (38) was used as the asymptotic population variance. Alternatively, one could also use an F-test for the differences in variances when the means are equal. In this case, the numerator is $\hat{\sigma}_k^2 = \sigma_k^2/k$ so that the ratio $\hat{\sigma}_k^2/\sigma_1 \sim F(N-k, N-1)$. The null hypothesis would be rejected if the ratio fell outside the two-tailed range of the F-distribution over a specified acceptance region.

Seasonality and the Variance Ratio Test

One of the concerns about pricing weather derivatives is the influence of seasonality on the random outcomes. Autocorrelation brought about by seasonal weather patterns can lead to rejections of hypotheses using the variance ratio test even if autocorrelation is spurious, as is found in heat waves and so on.

The impact of systematic seasonal influences cannot be ignored, but the effects can be removed. In this analysis, we have removed systematic weather patterns, leaving a path-dependent residual that resembles a random walk. To see this, define the daily temperature path above 65°F as a deterministic function of time, $g(t)$. In the current study, for example, $g(t) = E[W_t] = -0.38 + 0.21t - 0.002t^2$ is a quadratic that nicely fits the summer weather patterns in Toronto.

Given the definition of $g(t)$, the expected value of cumulative cooling degree-days at time $t = 0$ is:

$$(39)\quad W_0^* = \int_1^T g(t)\,dt.$$

After day 1, the actual degree-day is calculated and its deviation from expected is recorded. At the end of day 1,

$$(40)\quad W_1^* = g(1) + e_1 + \int_2^T g(t)\,dt,$$

and at the end of day 2,

$$(41)\quad W_2^* = \left[\int_1^2 g(t)\,dt + e_1 + e_2\right] + \int_3^T g(t)\,dt.$$

This can be generalized to any date $t \le T$ as:

$$(42)\quad W_T^* = \int_1^t g(t)\,dt + \int_1^t e_t\,dt + \int_{t+1}^t g(t)\,dt,$$

$$(43)\quad W_t^* = \int_1^T g(t)\,dt + \int_1^t e_t\,dt.$$

One can see from this process that the random part follows a walk over each time step, and is independent of the systematic influence of time. Specifically,

$$(44)\quad E\left[W_2^* - W_0^*\right] = E\left[W_2^* - W_1^* + W_1^* - W_0^*\right] = E\left[e_1 + e_2\right],$$

or more generally,

$$(45)\quad E\left[W_t^* - W_{t-k}^*\right] = ke_t,$$

as required for a random walk.

However, while this process is consistent with a random walk, the existence of a random walk still must be treated as a hypothesis. Recall that the function $g(t)$ removed non-systematic weather events such as heat waves or other extraordinary items which could cause year-specific transitory autocorrelation.

Transitory autocorrelation can be removed by averaging across years, but to do this the definition of the variance ratio must be modified accordingly. From the above results, the mean value of the k-lag error in each year was shown to be ke_t.

For a variety of risk-related reasons, the value of e_t will not necessarily equal $e_{t,n-1}$ or $e_{t,n+1}$. So, across N years the expected value of ke_t is:

$$(46) \quad k\mu_1 = e\left[ke_1\right] = \frac{1}{N}\sum_{n=1}^{N} ke_{1,n},$$

where the subscript n has been added to denote the year of the observation.

The variance of equation (39) is given by:

$$(47) \quad \sigma_k^2 = E\left[ke_1 - E[ke_1]\right]^2 = E\left[ke_1 - k\mu_1\right]^2 = k^2\left[e_1 - \mu_1\right]^2,$$

$$(48) \quad \sigma_k^2 = k^2\sigma_1^2.$$

This measure of σ_k^2 contrasts with the standard measure of $\sigma_k^2 = k\sigma_1^2$ in that the step multiplier k is squared. This results from averaging the mean lags from each year. However, since seasonality and spurious autocorrelation have been removed, the variance measure is unbiased and asymptotically efficient, and the variance ratio is specified as:

$$(49) \quad VR_a = \frac{\sigma_k^2}{k^2\sigma_1^2}.$$

Moreover, the Lo and McKinley (1999) asymptotic estimator still can be used to test the null hypothesis:

$$H_0: \frac{\sigma_k^2}{k^2\sigma_1^2} - 1 = 0.$$

Long-Run versus Short-Run Effects

Having resolved problems of seasonality and asynchronous autocorrelation, a final question to consider is whether the random walk hypothesis holds across a smaller number of years. Rather than averaging across the entire history of weather records (e.g., 1840–1996), a useful strategy would be to examine shorter (e.g., overlapping 30-year) time horizons. The benefits to doing this are to first determine if acceptance or rejection of a random walk is due to long versus short time horizons, and second to examine the persistence or frequency of the random walk over time. Each 30-year subsample can be considered an unbiased estimate of the larger population, but the asymptotic population variance is known. Therefore, the standard errors can be easily estimated.

The standard error of the sample $n < N$ is:

$$(50) \quad S_n = \left[\frac{2(2k-1)(k-1)}{3(N-1)k}\right]^{1/2} \Big/ \sqrt{n},$$

and this can be used in the denominator of a t-statistic with $n - 1$ degrees of freedom.

Variance Ratio Test Results

The variance ratio hypothesis was tested using daily data from 1840–1996 for 92 days in each year. The tests were conducted by first calculating the value $W_{t,n}^*$ for each day and across years, and then converting these data to logarithms. The results are presented in Table 4 for all years and five subperiods for lags of 1–10 days and lags of 35–40 days.

According to theory, a random walk would be rejected if the means of the k-lag difference or the variance of the k-lag difference are significantly different than the values of k in the first column of Table 4. Using $N = 92$ in the calculation of the asymptotic variance in equation (38) and calculating the test statistic Z in equation (37), there are no instances where the random walk is rejected. Using $N = 92$, the F-test fails to reject the null hypothesis that the variance ratio is significantly different than 1.0 in all cases.

Failure to reject the null hypothesis on the variance ratio occurs even though there is a visible departure in the computed value of k in Table 4 from the theoretical value of k. The reason for this observation is that the asymptotic variance increases with k. For example, when $k = 2$, the

Table 4. Estimated Value of Means and Variance Ratios (VRs) for 1840–1996 Study Period and Five Subperiods

	1840–1996		1840–1870		1871–1900	
Lag *K*	**Mean**	**VR**	**Mean**	**VR**	**Mean**	**VR**
1	1.00	1.00	1.00	1.00	1.00	1.00
2	1.99	2.01	2.00	2.01	2.01	2.00
3	2.99	3.02	3.00	3.03	3.03	3.01
4	3.99	4.04	4.00	4.06	4.06	4.03
5	4.98	5.06	5.00	5.09	5.09	5.07
6	5.97	6.09	6.00	6.14	6.14	6.11
7	6.96	7.13	7.00	7.21	7.18	7.16
8	7.95	8.15	8.01	8.30	8.22	8.21
9	8.95	9.23	9.02	9.40	9.26	9.26
10	9.97	10.30	10.03	10.54	10.32	10.32
35	35.47	31.05	36.07	42.07	38.99	40.99
36	36.47	40.22	37.11	43.28	40.22	42.27
37	37.46	41.58	38.14	44.50	41.44	43.56
38	38.47	42.55	39.16	45.75	42.69	44.86
39	39.47	43.73	40.16	47.02	43.95	46.15
40	40.48	44.90	41.50	48.27	45.20	47.46

Notes: The variance ratio (VR) is $\sigma_k^{*}/k\sigma_1^2$, and the mean ratio is $\mu k_k/\mu_1$.

asymptotic variance for $N = 92$ is 0.011, but for $k = 40$ it is 0.34. Therefore, even though the 48.27 value of σ_{40}^2/σ_1^2 in the 1840–1870 subperiod is 8.27 points above the theoretical value of 40, the normalized variance ratio test $(\sigma_{40}^2/k^2\sigma_1^2 - 1)/\sigma_z$ is equal to 1.20, which falls below the critical value of 1.96 at the 5% level.

To examine whether the results in Table 4 are a consequence of chance or sampling, the variance ratios were also calculated for overlapping 30-year periods and the null hypothesis was tested using the *t*-statistic which accounts for possible sampling error. The standard error is defined in equation (50), which divides the Lo and McKinley asymptotic variance measure by the square root of 30 (years). Of 128 overlapping time periods, in no case was the null hypothesis rejected at the 5% level for up to 29 lags, and only one violation beyond that. Repeating the analysis for 20- and 10-day lags revealed that at 20 lags there were 29 rejections for an acceptance rate of 80.4%, and at 10 lags there were 37 of 148 rejections for an acceptance rate of 75%.

The results offer strong support for the random walk hypothesis about the seasonal trend even when a small number of years are considered. But within this result also resides the caveat that to truly smooth individual year effects, at least 30 years should be considered in practice. Failure to reject the random walk also implies that volatility jumps are probably not of great concern. This does not imply volatility is a constant value, but it does imply that an average value of volatility across years ($E[\sigma]$) is an unbiased estimate of volatility. Furthermore, given the evidence presented in Table 3, the estimate $E[\sigma]$ will be consistent and efficient. The evidence suggests that the option pricing model proposal in this study is appropriate for the pricing of degree-day weather options.

Table 4. Extended

	1901–1930		1931–1960		1961–1996	
Lag *K*	**Mean**	**VR**	**Mean**	**VR**	**Mean**	**VR**
1	1.00	1.00	1.00	1.00	1.00	1.00
2	2.00	2.01	2.01	2.03	2.01	2.00
3	3.01	3.02	3.02	3.08	3.04	3.01
4	4.00	4.04	4.03	4.14	4.07	4.02
5	4.95	5.06	5.03	5.23	5.11	5.03
6	5.87	6.09	6.03	6.32	6.15	6.05
7	6.79	7.12	7.05	7.41	7.18	7.10
8	7.71	8.17	8.08	8.52	8.20	8.19
9	8.65	9.23	9.12	9.65	9.22	9.22
10	9.62	10.29	10.18	10.80	10.23	10.24
35	30.39	38.50	37.27	41.56	37.74	40.85
36	31.31	39.67	38.35	42.75	39.01	42.03
37	32.23	40.82	39.41	43.91	40.28	43.20
38	33.12	41.94	40.47	45.06	41.54	44.38
39	34.01	43.18	41.51	46.23	42.79	45.57
40	34.95	44.37	42.56	47.41	44.02	46.77

Estimates of Cooling Degree-Day Option Premia

This section reports actual option premiums calculated for Toronto, Ontario. The contracts considered are 92-day put and call options with contract terms from June 1 with an expiry on August 31. Each tick in-the-money (θ) was valued at $5,000 per degree-day. Several empirical considerations are illustrated in the results.

First, premium estimates are calculated using both the inter-year "burn-rate" method used in the insurance industry [equation (14)] and the intra-year Black's option pricing model [equations (21) and (24)]. Second, in order to illustrate the importance of "relevant time horizon," estimates are provided for the 1840–1996 data period and the 1930–1996 subperiod. Third, because the options pricing model is sensitive to the initial index value (W_0^*), using a simple average in all cases would not be prudent. For the options pricing model only, a range of initial values of W_0^* are examined. This type of sensitivity analysis is important because weather agencies such as Environment Canada and the U.S. Weather Service cannot generally predict forward temperatures with reasonable accuracy. However, they can and do provide three- or four-month forecasts that state whether conditions are going to be normal, below normal, or above normal. If the prediction is above normal, for example, the buyer of a call may want to increase the initial expectation of W_T^* to match the forecast and reduce the premium.

Tables 5 and 6 for 1840–1996 and 1930–1996, respectively, present results for base case at-the-money option pricing calculations as well as a range of strike prices above and below this value. The at-the-money strike is defined as the average cooling degree-days across the years sampled. This value is 379.39 for 1840–1996, and 489.50 for 1930–1996.

Table 5. European Options and Burn-Rate Premiums, 1840–1996 (Tick = $5,000)

Strike Price	Option Value		Burn Rate		Maximum Payoff	
	Put	Call	Put	Call	Put	Call
200	0	882,374	18,215	915,190	464,500	2,935,100
250	0	636,438	63,647	710,420	714,500	2,685,100
300	692	391,264	135,264	533,239	964,500	2,435,100
350	23,156	167,718	229,910	376,885	1,214,500	2,185,100
379.39	77,073	77,073	297,054	1,361,450	2,038,150	2,038,150
400	139,950	38,574	352,121	249,096	1,464,500	1,935,100
450	351,674	4,361	508,943	155,918	1,714,500	1,685,100
489.50	542,100	497	657,130	106,788	1,912,000	1,487,600
500	539,513	263	698,560	95,534	1,964,500	1,435,100
550	839,198	10	908,806	55,781	2,214,500	1,185,100
600	1,085,126	0	1,136,421	33,405	2,464,500	935,100
650	1,331,062	0	1,370,114	17,089	2,714,500	685,100

The option premiums differ between the options model and the burn-rate model as well as across the two time periods.

When the sampling period was represented from 1840, the at-the-money put and call price was $77,073 for the 379-CDD strike option model, and approximately $297,054 for the burn-rate model (Table 5). The maximum payoff for the put option under either case would have been $2,038,150 for the put option and $2,038,150 for the call option. As the strike price was increased, put options would be issued in-the-money and the put option premiums would rise as the call premiums fell. For a strike of 600 CDD, the option model put premium was $1,085,126, while for the burn-rate model it was $1,136,421. The maximum put payoff increased to $2,464,500. The corresponding call option for the option model was $0, and for the burn-rate model it was $33,405. The maximum payoff that would have possibly occurred with this strike over this period was $935,100. A lower than average strike implies that put options are issued out-of-the-money, while call options are issued in-the-money. At a strike of 250 CDD, the put options price is negligible, while the call option price is $636,438. Under the burn-rate model, the corresponding put and call prices were $63,947 and $710,420, with maximum payoffs of $714,500 for the puts and $2,685,100 for the calls.

A similar pattern was observed for the 1930–1996 period (Table 6). The at-the-money option price (489.50 CDD) for the put and call was $83,835, and under the burn-rate model the respective put and call prices were $220,358 and $220,370. The maximum put and call payoffs would have been $1,516,900 and $1,487,600, respectively. For in-the-money calls with a strike of 250 CDD, the call option was $1,178,041 and the corresponding put was $0. The burn-rate put and call prices were $4,767 and $1,202,279, respectively, with maximum payoffs of $319,400 and $2,685,100. For in-the-money puts at 600 CDD, the put option price was $544,298, and the call price was only $776. The burn-rate premiums were $624,900 and $72,412 for the put and call, respectively, with corresponding maximum payoffs of $2,319,400 and $685,100.

These results illustrate some important and critical details regarding the pricing of degree-day derivatives and the selection of a time period over which to analyze heat. The difference between options pricing and burn-rate models is striking, especially when priced at-the-money.

Table 6. European Options and Burn-Rate Premiums, 1930–1996 (Tick = $5,000)

Strike Price	Option Value		Burn Rate		Maximum Payoff	
	Put	Call	Put	Call	Put	Call
200	0	1,423,978	1,035	1,448,548	69,400	2,935,100
250	0	1,178,041	4,767	1,202,279	319,400	2,685,100
300	0	932,103	8,498	956,010	569,400	2,435,100
350	2.52	686,168	20,119	717,631	819,400	2,185,100
379.39	94	541,697	841,749	39,261	2,319,400	685,100
400	670	440,897	50,519	498,031	1,069,400	1,935,100
450	17,974	212,266	121,639	319,150	1,319,400	1,685,100
489.50	83,835	83,835	220,358	220,370	1,516,900	1,487,600
500	113,047	61,400	249,622	197,134	1,569,400	1,435,100
550	306,996	9,411	417,813	115,325	1,819,400	1,185,100
600	544,298	776	624,900	72,412	2,069,400	935,100
650	789,497	37	841,749	39,261	2,319,400	685,100

Using the 1840–1996 period, the burn-rate model prices the insurance at 3.85 times the option pricing model, whereas for the 1930–1996 period the pricing multiple is 2.63. The ratio converges to 1 for policies that are in-the-money, and infinity for options out-of-the-money. The results illustrate why different approaches to pricing weather options can yield large bid-ask spreads.

The explanation for these differences lies in how risk is measured and what risks are actually being traded. The burn-rate model assumes that history will repeat itself and the variability and probability distribution of the past will be replicated in the future. It rests upon an actuarial structure, which is seemingly predictable, but one which also carries with it some significant variability. In contrast, the options pricing model is not backward-looking in the sense of a memorized historical probability distribution. It assumes infinite random weather patterns, which can occur in any season. The role of history is vague only in its use to establish seasonal norms and a range of volatility measures—but once these are established, history's role is done.

Another key difference is the assumption of a starting point. The options pricing model assumes a numerical starting position from which variability in a weather index is measured, and the price of the option is sensitive to this initial position. For example, the further the index strike is below the initial index value, the higher will be the value of a call option and the lower will be the value of a put option. Because the burn-rate model's principal Gaussian assumption is that history will repeat itself, the burn-rate model does not require an estimate of the initial weather index value per se.

As discussed above, the initial assumption regarding the forward weather index is crucial to the accurate pricing of options. Tables 5 and 6 present results assuming that the initial index value is equal to the historical mean. In reality, however, this may not be the case. Weather forecasts may predict higher or lower than normal temperatures, and this will have a conditional impact on the initial index value. For example, the mean growing degree-days for the 1930–1996 period was 489.50, with a range from 186 to 787 and a standard deviation of 114 (Table 1). If the long-range weather forecast was for warmer than usual weather, then it would be prudent to increase the initial index value accordingly so that the likelihood of a put option ending in-the-money is lower

and the likelihood of the call ending in-the-money is higher. Likewise, if the long-range forecast was for cooler than normal weather, then the index would be decreased such that the likelihood of a put ending in-the-money would increase and the likelihood of a call ending in-the-money would decrease.

Table 7 presents option pricing sensitivity results for the 1840–1996 period, and Table 8 reports results for the 1930–1996 period. Since the burn-rate model does not rely on initial conditions, only the option pricing model is considered. Each column in Tables 7 and 8 represents a percentage of the mean, with 1.00 representing the mean, 0.50 being 50% of the mean, and 150% being 50% higher than the mean. As predicted by options theory, as the initial condition decreases, the put option value increases and the call option value increases, holding the strike level constant. For example, if the strike level is 400 CDD, the value in Table 7 for the 1840–1996 period for a put option is $1,034,468, and for the call price is $0 if the weather forecast implies cumulative degree-days will be 50% less than average. If the cooling trend is believed to be less severe, say 75%, then the put value for a 400-CDD strike decreases to $567,929 and the call price is $23. If the weather prediction calls for a 50% increase in cooling degree-days, then the likelihood that a 400-CDD put option will expire in-the-money is nil, and the put option is priced at $21. In contrast, the likelihood of the call option expiring in-the-money rises, and the call option premium increases to $831,708. A similar pattern is illustrated for the 1930–1996 period in Table 8.

Conclusions

Focusing on two related issues, this analysis has examined the pricing methods of degree-day derivatives. First is the issue of pricing. It is argued here that an equilibrium model along the Black-Scholes line can be used to price degree-day derivatives assuming zero drift (justified on expectations) and zero market price of risk (justified on diversifiable risk). The second related issue is that on expectation a degree-day index satisfies (at least for the example provided) the required conditions for a random walk and geometric Brownian motion. Notably, if the analysis failed to support a Brownian motion in degree-day dynamics, this would also have led to a rejection of the proposed pricing model as a viable candidate.

Recent papers by Richards, Manfredo, and Sanders (2004), Cao and Wei (2004), and others have argued against the use of a Black-Scholes type model for a variety of reasons, including measurement of the market price of risk and volatility jumps. The results of the current investigation cannot be used to refute their claims, since the data source is different, but importantly the findings of this paper indicate that general rejections of Brownian motion cannot be justified as a matter of course. This still leaves open the academic debate over the market price of risk. The complexity of models such as those of Cao and Wei (2004), and Richards, Manfredo, and Sanders (2004), illustrate the economic significance of the measure to equilibrium pricing.

This debate will no doubt continue, but the assumption used in this study is that because specific-locale weather risks would be fully diversifiable in an equilibrium market context (such as CAPM), the market risk premium should be zero. Some may argue against the use of zero-beta to make such a claim, but from a theoretical point of view one cannot separate a CAPM equilibrium from a Cox-Ross equilibrium since the two equilibria must coexist as one.

The approach used here differs markedly from an insurance approach to pricing weather derivatives. The "burn-rate" approach prices premiums based upon what would have occurred over a recent time period. It was pointed out that the key difference between the burn-rate model and the options pricing model is in how risk is defined.

Table 7. Sensitivity of Options Prices to Initial Conditions, 1840–1996

	Percentage of Mean									
	0.50		0.75		1.00		1.25		1.50	
Strike	Put	Call	Put	Call	Put	Call	Put	Call	Put	Call
200	69,975	19,287	10	415,853	0	882,375	0	1,348,906	0	1,815,437
250	296,757	132	6,873	176,779	1	636,438	0	1,102,968	0	1,569,499
300	542,563	0	104,962	28,931	692	391,192	0	857,031	0	1,323,562
350	788,500	0	323,336	1,367	23,156	167,718	100	611,193	0	1,077,624
400	1,034,468	0	567,929	23	139,950	38,574	4,644	369,800	21	831,708
450	1,280,375	0	813,844	0	351,674	4,361	46,048	165,266	1,039	586,788
500	1,526,313	0	1,059,781	0	593,513	263	174,937	48,218	13,747	353,559
550	1,772,250	0	1,305,719	0	839,198	10	381,556	8,900	72,838	166,712
600	2,018,188	0	1,551,656	0	1,085,126	0	619,676	1,081	209,925	57,861
650	2,264,125	0	1,797,594	0	1,331,063	0	864,624	92	412,954	14,593

Table 8. Sensitivity of Options Prices to Initial Conditions, 1930–1996

	Percentage of Mean									
	0.50		0.75		1.00		1.25		1.50	
Strike	Put	Call	Put	Call	Put	Call	Put	Call	Put	Call
200	335	220,449	0	822,046	0	1,423,978	0	2,025,910	0	2,627,842
250	56,523	30,700	0	576,109	0	1,178,041	0	1,779,973	0	2,381,904
300	272,149	388	502	330,673	0	932,103	0	1,534,035	0	2,135,967
350	517,699	0	28,254	112,488	2.52	686,168	0	1,288,098	0	1,890,030
400	763,636	0	175,874	14,170	670	440,897	0	1,042,160	0	1,644,092
450	1,009,573	0	408,223	582	17,974	212,266	12	796,234	0	1,398,155
500	1,255,510	0	653,588	9	113,047	61,400	837	551,122	0	1,152,217
550	1,501,448	0	899,516	0	306,996	9,411	13,374	317,721	33	906,313
600	1,747,386	0	1,145,454	0	544,298	776	77,173	135,584	1,004	661,346
650	1,993,323	0	1,391,391	0	789,497	37	226,707	35,180	10,968	425,373

Under the burn-rate model, it is assumed history will repeat itself with the same likelihood, but not necessarily the same order, as the time horizon selected for pricing. In other words, the approach assumes the relevant measure of risk is the inter-year variability in weather.

The options pricing model developed in this study makes no such assumption, and is in fact based on intra-year risks. As with conventional options pricing, volatility and the initial value of the weather index are the key drivers of risk. History is used only to measure volatility and to determine a range of index values, but once a measure of volatility is selected and the initial condition determined, history has no further role to play in the pricing process. For example, the 1840–1996 period had mean cooling degree-days (above 65°F) of 379 CDD and an annualized volatility of 20.63% for the period June 1 to August 31. Using the 1930–1996 period, the average cooling degree-days was 489 CDD with a volatility of 17.39%. Under no year was volatility found to exceed 29.6%, yet the implied volatility that would equate the options pricing model to the burn-rate model was 80% for the 1840–1996 period and 45.8% for the 1933–1996 period.

Findings reveal a significant and often large difference between the burn-rate model and the options pricing model, particularly for products priced at or near-the-money. It was shown that the burn-rate model prices options as much as two to three times higher than the options pricing model. The two approaches converge only for options priced in-the-money or out-of-the-money. This is consistent with the various theories of pricing non-traded assets in equilibrium, and in a risk-neutral economy. Statistical analyses confirmed that the underlying assumptions required for pricing degree-day weather options are empirically valid.

The options pricing model presented in this study is new. On one hand, it is an improvement over the traditional burn-rate approach in that it places much more emphasis on risk; and for a derivatives market which is essentially designed to manage the buying and selling of risk, there can be efficiency and liquidity gains if the model is implemented in practice. On the other hand, the traditional approach is easy to implement and even easier to comprehend. However, if a formal derivatives market for weather insurance is going to emerge, the approach developed in this study is very likely to provide foundation for pricing weather derivative products.

Finally, one must ask in a practical manner what this study implies for risk management in agriculture. If a crop insurer such as the U.S. Risk Management Agency were to institute heat insurance, even as a pilot, the beneficiaries would likely be farmers whose major source of risk is directly related to heat events. The deterioration of oil quality in soybeans under high temperatures, for example, is a specific-event risk for producers who have contracted under a quality rating and who may not benefit from crop insurance. While the yield of soybeans may not be severe, the volumetric risk here is tied to the quantity and quality of oil.

It is unclear at this time whether the U.S. Risk Management Agency (RMA) will ultimately consider the use of weather insurance in general. However, should it consider doing so, the model presented in this study provides a good starting point for assessing the pricing mechanism. This of course applies only to crop losses due to excessive temperatures. The model cannot and should not be used for other weather factors, such as rainfall, because of discontinuities in the time paths. Nevertheless, this paper has shown that weather insurance is not only viable as a substitute for assessing specific-event risk in agriculture based on agronomic measures such as growing degree-days, but also provides results toward understanding how to best price these products in practice. In the broader context, even if the RMA does not

consider offering weather insurance to farmers, the Agency may want to consider incorporating weather risk management into the reinsurance agreement. Because of the systematic correlation between loss ratios and weather events, less costly reinsurance might result. But whether tying reinsurance to specific weather events is either efficient or equitable is a matter for further investigation.

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Mean Reversion and Autocorrelation in Profitability of Illinois Farms

Jill M. Phillips and Ani L. Katchova

Abstract

Economic theory implies that firms in a competitive market will adjust to long-run equilibrium levels of profitability, resulting in mean reversion of profitability. Partial adjustment models are applied to farm-level data from Illinois to test for mean reversion and autocorrelation in profitability. Results show that farm businesses revert to individual levels of expected profitability at an annual rate of 0.5, while the annual rate of negative autocorrelation is 0.175.

Key words: autocorrelation, mean reversion, partial adjustment, profitability

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In a perfectly competitive market, firms produce a homogeneous product, and each firm's relative size is insignificant so that individual firms have no influence on the market price. In the long run, the number of firms in a perfectly competitive market will vary over time in response to economic opportunities that allow them to maximize profits.

The assumption of free entry and exit suggests new firms will enter the market when economic profits are positive, while firms will exit the market when profits are negative. These conditions provide for a long-run equilibrium rate of return on investment for all firms in the market. The assumptions of perfect competition and free entry and exit imply that firms operating in such a market experience mean-reverting profitability. Mean reversion refers to the tendency of profitability to return to the long-run equilibrium level, indicating changes in profitability may be predictable.

Agriculture is an ideal testing ground for the theory of mean reversion of profitability since farm businesses are price-takers in a highly competitive market. We extend the existing literature by applying a partial adjustment model to farm profitability to determine the extent to which profitability is mean-reverting and autocorrelated. In the following sections, we define the partial adjustment model, address data issues, present the results, and discuss the implications.

Farm profitability is of great interest to a diverse group of people, including farmers, input providers, output users, agricultural lenders, government agencies, and policy makers. Dissection of the driving forces

behind fluctuations in farm profitability, such as mean reversion and autocorrelation, will lead to more realistic models of long-term farm profitability.

Partial Adjustment Model

Fama and French (2000) utilized a partial adjustment model to analyze mean reversion in the profitability of NYSE, AMEX, and NASDAQ firms from 1964 to 1996. Their results showed that profitability reverted at an annual rate of approximately 0.38, with an annual autocorrelation effect of 0.09, when firms adjusted to an individual level of expected profitability. Testing the assumption that all firms reverted toward one industry-wide equilibrium level of expected profitability, Fama and French found that the profitability of all firms reverted to the industry-wide mean at a rate of 0.3, and the effects of autocorrelation increased to 0.13.

Following Fama and French (2000), we estimate an annual cross-sectional partial adjustment regression for the change in profitability from year t to $t+1$. To test for the presence of mean reversion and autocorrelation in farm profitability, we first assume all farm businesses adjust to an individual level of profitability. This assumption is tested by estimating the following regression for every year in our sample:

$$(1)\quad R_{i,t+1} - R_{i,t} = a_0 + a_1[R_{i,t} - E(R_{i,t})] + a_2[E(R_{i,t}) - E(R_t)] + a_3[R_{i,t} - R_{i,t-1}] + e_{i,t+1}.$$

In this model, $R_{i,t}$ is our measure of profitability, where i represents each farm in the sample and t represents the year. The dependent variable ($R_{i,t+1} - R_{i,t}$) is the current change in profitability from t to $t+1$. The deviation from expected individual profitability is measured by $R_{i,t} - E(R_{i,t})$, and the deviation of expected individual profitability from expected global profitability is measured by $E(R_{i,t}) - E(R_t)$. The lagged change in profitability from $t-1$ to t, i.e., $R_{i,t} - R_{i,t-1}$, represents the possible effects of autocorrelation (Fama and French, 2000).

This partial adjustment model for profitability combines the effects of the deviation of the farm profitability from the expected individual profitability, $R_{i,t} - E(R_{i,t})$, and the lagged change in profitability, $R_{i,t} - R_{i,t-1}$. The lagged change in profitability is included to test whether the deviation from expected profitability represents the sole source of variation in profitability. We expect the coefficient of the individual deviation term (a_1) to be negative and larger in absolute value than the coefficient of the lagged change in profitability (a_3), which should also be negatively related to the current change in profitability, based on Fama and French's (2000) results. The smaller a_3 is, the less influence the lagged change has on the current change in profitability. If a_1 has a larger absolute value than a_3, then mean reversion has a greater effect on the current change in profitability than does the lagged change in profitability. We expect this to be the case because economic theory implies that firms in a competitive market will adjust to a long-run level of profitability.

We also test the restriction $a_1 = a_2$. If this is the case, then the two independent variables can be combined to yield the deviation of profitability from expected industry-wide profitability, $R_{i,t} - E(R_t)$. The new model is defined as:

$$(2)\quad R_{i,t+1} - R_{i,t} = b_0 + b_1[R_{i,t} - E(R_t)] + b_2[R_{i,t} - R_{i,t-1}] + \varepsilon_{i,t+1}.$$

The rates of mean reversion are predicted to differ between the two models since the proxy for expected individual profitability in model (1) accounts for differences in risk and structural characteristics across farm businesses. As before, the coefficient of deviation from expected industry-wide profitability (b_1) is expected to be negatively related to the current change in profitability. Again, the coefficient on the lagged change in profitability (b_2) is

hypothesized to be relatively small compared to b_1, and inversely related to the current change in profitability.

Fama and French (2000) found that the firms in their study adjusted more quickly to individual levels of profitability than a global profitability level. Based on their results, we expect that the absolute value of a_1 will be larger than the absolute value of b_1. As noted by Fama and French, if model (1) produces a significantly different rate of mean reversion than model (2), then the expected individual profitability proxy captures important differences across farm businesses in expected profitability.

Proxy for Expected Profitability

Model (1) and model (2) include expected individual profitability, $E(R_{i,t})$, and expected industry-wide profitability, $E(R_t)$, which are estimated from the data. In this study, we follow Foreman and Livezey (2003) and Gloy, Hyde, and LaDue (2002) in utilizing the rate of return on farm assets as a proxy measure for farm profitability.[1,2,3] Expected individual profitability is predicted using the following model:

$$(3) \quad E(R_{i,t}) = f(AGE_{i,t}, AGESQ_{i,t}, OER_{i,t}, TEN_{i,t}, CRSC_{i,t}, ASSETS_{i,t}),$$

where i represents farm and t represents year. Operator age (*AGE*), operator age squared (*AGESQ*), operating expense ratio (*OER*), tenure (*TEN*), credit score (*CRSC*), and assets (*ASSETS*) serve as financial and nonfinancial independent variables, based on previous farm profitability studies (Barry, Escalante, and Bard, 2001; Ford and Shonkwiler, 1994; Foreman and Livezey, 2003; Garcia, Sonka, and Yoo, 1982; Mishra, El-Osta, and Johnson, 1999; Mishra, El-Osta, and Steele, 1999; Plumley and Hornbaker, 1991; and Sonka and Thorpe, 1991). Definitions, means and standard deviations for the independent variables, and our measure of profitability (return on assets) are reported in Table 1.

Expected industry-wide profitability $E(R_t)$ is estimated as the mean profitability for all farms (the global mean), which is extracted from a naïve model where we regress $R_{i,t}$ on a constant. Fama and French (2000) found that firms in their sample had a lower rate of mean reversion when expected profitability was assumed to be at the global level than when firm-specific expected profitability was included in the partial adjustment model. Based on these previous results, we expect farms will adjust more quickly to an individual level of profitability than to a global level.

Comparison Between Age Groups and Credit Risk Groups

Barry, Bierlen, and Sotomayor (2000) used a similar model to test for partial adjustment in credit usage of farm businesses. Their partial adjustment term measured the speed at which borrowers adjusted to short-term and long-term debt levels. The coefficients on the specific independent variables in their study were negative and significant, implying farms in the sample followed the partial adjustment financial structure. The coefficient on the short-term debt partial adjustment term was significantly larger than that of the long-term debt partial adjustment term, suggesting farmers adjusted more quickly to a short-term level of debt than to a long-term level.

Barry, Bierlen, and Sotomayor (2000) also applied the models to separate groups to

[1] Our profitability measure, return on assets, measures profitability of the farm business, not the profitability of the farm operator or owner. Farm-level data on land appreciation values are not available within our data set. Thus, our measure of profitability does not account for capital gains on farmland or economic returns to the farm owner.

[2] Total assets are adjusted for the value of leased land, calculated as the product of the farm leased acres and the average Illinois farmland price for each year. This adjustment was needed so that two farms which are identical except for their leverage and land leasing would have the same return on assets.

[3] An alternative measure of profitability, return on equity, is also considered later in this study.

Table 1. Definitions of Variables and Descriptive Statistics

Variable	Description	Mean	Standard Deviation
AGE	Operator age (years)	48	11
AGESQ	Operator age squared	2,420	1,095
OER	Operating expense ratio: Total operating expenses divided by gross revenues	0.65	0.17
TEN	Tenure: Owned acres divided by total acres farmed	0.22	0.26
CRSC	Credit score: A categorical variable ranging from 1 for low credit risk to 5 for high credit risk	2.33	1.23
ASSETS	Total farm assets ($)	883,960	710,350
$R_{i,t}$	Rate of return on assets: Net farm income plus interest expense minus unpaid operator labor and management divided by average total farm assets	0.03	0.03

determine if the rate of adjustment differed by operator age and farm credit risk. They hypothesized that because older farmers generally had longer relationships with lenders, greater accumulations of equity, and stronger financial measures, they were less financially constrained than younger farmers. Likewise, farmers with low credit risk (indicated by low credit scores) generally have accumulated more financial resources and were less likely to experience asymmetric information in their relationships with lenders. Therefore, these farms were less financially constrained than those with high credit risk. Results from their analysis revealed older farmers and farms with low credit risk adhered more closely to the partial adjustment models.

We follow Barry, Bierlen, and Sotomayor (2000) in comparing differences in the rate of mean reversion and autocorrelation across different age groups. The two groups represent the youngest one-third (40 years and younger) and oldest one-third (55 years and older) of the farm operators in the sample. Older farmers are hypothesized to exhibit lower rates of mean reversion than younger farmers. This assumption is based on the increased management experience, stronger financial position, and greater resource availability of older farmers.

We also compare differences in the rate of mean reversion and autocorrelation across different credit risk groups. Credit risk for farm businesses is calculated with a credit score model based on financial ratios (solvency, repayment capacity, profitability, liquidity, and financial efficiency) recommended by the Farm Financial Council. The two groups represent the lowest one-third of credit risk (with credit scores lower than 1.6) and highest one-third of credit risk (with credit scores higher than 3.3) for the farms in the sample. The farms with low credit risk, which are generally less financially constrained, are expected to exhibit higher rates of mean reversion compared to those of high credit risk farms, because low credit risk farms have accumulated more financial resources and are subject to less asymmetric information.

Data Issues

Values for dependent and independent variables for the partial adjustment models (1) and (2) and expected profitability model (3) are based on annual farm-level observations from the Illinois Farm Business Farm Management Association for the years 1985–2002. We use ordinary least squares (OLS) regression for each year in the sample, yielding 16 cross-sectional

regressions for 1986–2001 for the partial adjustment models, and 18 cross-sectional regressions for 1985–2002 for the expected profitability model.

The coefficients of each independent variable and the intercept are averaged across the cross-sectional regressions. Standard deviations are then calculated for each independent variable as the square root of the squared differences between the mean coefficient and annual coefficients of each variable, divided by the number of regressions minus one. Given the mean coefficients and the standard deviations of the coefficients, *t*-statistics are computed for the coefficient means.

According to Fama and French (2000), this approach allows for the use of large samples of farm businesses and retains the power of cross-sectional tests. Fama and MacBeth (1973) utilized a similar approach to test a two-parameter portfolio model, while Barry, Escalante, and Bard (2001) employed a combined cross-sectional/time-series approach in their analysis of economic risk and the structural characteristics of farm businesses.

Our approach is similar to that of an unbalanced pooled cross-sectional/time-series sample, where each year a new random sample is drawn from the population (Wooldridge, 2002). In this case, we can assume independence, and occurrence of farm businesses in more than one year is treated as coincidental.

Unbalanced panel data are more favorable for our study than balanced panel data because the survivorship bias is mitigated. The profitability patterns of long-term survivors, represented by the farm businesses in the balanced panel set, are not necessarily representative of the entire data set or the general farm business population. In addition, there are only 20 farm businesses present in our data set for the entire period. Regressions based on so few annual observations, as opposed to average cross-sectional observations of 1,490, would likely yield statistically weak results.[4]

The cross-sectional/time-series approach also allows us to retain the effects of estimation error, present in the standard errors of the mean coefficients, due to correlation of the residuals across farm businesses. The use of panel data assumes the error in each time period is uncorrelated with the explanatory variables in the same time period (Wooldridge, 2002). Fama and French (2000) argued, however, that the year-by-year variation in the mean coefficients should include the effects of estimation error due to the correlation of residuals across farm businesses. The effects of estimation error can be attributed to an unobserved idiosyncratic error or disturbance, which in this case captures unobserved characteristics of individual farm businesses across time (Wooldridge, 2002). Thus, the cross-sectional/time-series approach utilized in our study allows for the residuals to differ by farm businesses, and preserves the correlation effects between the explanatory variables and the residuals over time.

Results

First, the results of the expected profitability models are presented. Results of the naïve model for $E(R_t)$ show the global mean for the farm profitability is 0.03. The coefficients and corresponding *t*-statistics of expected profitability model (3) are reported in Table 2. The coefficient on the operating expense ratio is negative and significant. This result confirms the findings of earlier studies (Ford and Shonkwiler, 1994; Mishra, El-Osta, and Steele, 1999; Plumley and Hornbaker,

[4] In estimating the partial adjustment model, we use only observations of farm businesses that are present in the data set for a minimum of three consecutive years, $t-1$, t, $t+1$. This requirement introduces survivorship bias to the model but cannot be avoided in this case. Our sample drops from 26,821 observations in model (3) to 11,738 observations in models (1) and (2).

Table 2. Regression Results for the Expected Profitability Model

Variable [a]	Expected Profitability Model (3)
Intercept	0.091***
	(3.96)
AGE	0.0003
	(0.48)
AGESQ	-6.7E-6
	(-1.21)
OER	-0.105***
	(-11.61)
TEN	0.016
	(1.31)
CRSC	0.001
	(0.62)
ASSETS	3.1E-9
	(0.55)
Adjusted R^2	0.36
Number of Observations	26,821

Notes: Triple asterisks (*) denote statistical significance at the 1% level, based on a two-tailed *t*-test. Coefficients are averaged from cross-sectional regressions for 1985–2002. Numbers in parentheses are *t*-statistics.

[a] The dependent variable is rate of return on assets ($R_{i,t}$).

1991; and Sonka and Thorpe, 1991), suggesting the operating expense ratio is inversely related to farm profitability.

The mean coefficients and corresponding *t*-statistics of partial adjustment models (1) and (2) are displayed in Table 3. In model (1), we estimate the rates of mean reversion and autocorrelation when farm businesses are assumed to adjust to individual levels of expected profitability. Results show that the profitability of farm businesses has a mean-reverting rate of 0.497. This rate is larger than that reported by Fama and French (2000), whose analysis produced a rate of mean reversion of 0.38 under the above assumptions. The lagged change in profitability has a coefficient of -0.178 in this model, a higher rate of negative autocorrelation than Fama and French's result of -0.09.

Table 3. Regression Results for the Partial Adjustment Models

Variable [a]	Model (1)	Model (2)
Intercept	-0.003	-0.002
	(-0.18)	(-0.16)
$R_{i,t} - E(R_{i,t})$ [b]	-0.497*	
	(-1.69)	
$E(R_{i,t}) - E(R_t)$ [c]	-0.490***	
	(-2.93)	
$R_{i,t} - E(R_t)$ [d]		-0.500**
		(-3.22)
$R_{i,t} - R_{i,t-1}$ [e]	-0.178*	-0.175*
	(-1.71)	(-1.65)
Adjusted R^2	0.36	0.32
No. of Obs.	11,738	11,738

Notes: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed *t*-test. Coefficients are averaged from cross-sectional regressions for 1986–2001. Numbers in parentheses are *t*-statistics.

[a] The dependent variable is change in return on assets from t to $t+1$ ($R_{i,t+1} - R_{i,t}$).

[b] $R_{i,t} - E(R_{i,t})$ is the deviation of the rate of return on assets from the individual mean.

[c] $E(R_{i,t}) - E(R_t)$ is the deviation of the individual mean from the global mean.

[d] $R_{i,t} - E(R_t)$ is the deviation of the rate of return on assets from the global mean.

[e] $R_{i,t} - R_{i,t-1}$ is the change in the rate of return on assets from $t-1$ to t.

The coefficient on the deviation of profitability from expected individual profitability (-0.497) and the coefficient on the deviation of expected individual profitability from expected global profitability (-0.490) are not significantly different from each other. Therefore, the two independent variables are added together to define the deviation of farm profitability from expected industry-wide profitability, used in model (2).

Table 3 also reports the results from model (2), where expected farm profitability is approximated by the mean profitability for all farms estimated by the naïve model. The rate of mean reversion is found to be 0.5, with a rate of negative autocorrelation of 0.175. These rates are

once again higher than Fama and French's results of 0.3 and 0.13 for mean reversion and negative autocorrelation rates, respectively. The significance of the lagged change in profitability implies there is negative autocorrelation in profitability in our sample beyond what can be predicted by the deviation from expected profitability. The larger coefficient on lagged change in profitability in our study suggests lagged profitability may play a larger role in predicting profitability for farm businesses compared to firms in other industries.

As shown by results from model (2), the extent to which profitability reverts depends on the difference between the farm past profitability and the industry-wide mean profitability, and is not affected by the farm mean profitability. These results are contrary to our hypothesis based on Fama and French's (2000) findings,[5] and evoke interesting questions. The proxy for individual expected profitability is included as an independent variable in partial adjustment model (1) because we expect this variable to collect meaningful differences in expected profitability across farms.

Due to the risks associated with weather, the intense use of capital, and the large number of farm businesses, agriculture is a unique industry. All of these characteristics, in addition to macroeconomic factors and government policies, interact in a unique way to influence the variation of farm profitability. Many of these factors have homogeneous effects across all farm businesses, which may explain why the industry rate of mean reversion is similar to that of individual farms. Overall, the results from these models show that both mean reversion and autocorrelation in profitability are present for Illinois farmers.

[5]These results may also reflect differences in sample composition. Our sample is primarily comprised of Illinois grain farms, while a relatively smaller concentration of livestock and multiple-enterprise farms are also included in the data. Fama and French's sample of NYSE, AMEX, and NASDAQ firms was likely more heterogeneous than our sample.

Table 4. Regression Results with Alternative Definition of Profitability as Return on Equity

Variable [a]	Model (1)
Intercept	-0.020 (-0.36)
$R_{i,t} - E(R_{i,t})$ [b]	-0.637 (-0.74)
$E(R_{i,t}) - E(R_t)$ [c]	0.066 (0.03)
$R_{i,t} - R_{i,t-1}$ [d]	-0.278 (-0.55)
Adjusted R^2	0.38
No. of Obs.	11,738

Notes: Coefficients are averaged from cross-sectional regressions for 1986–2001. Numbers in parentheses are *t*-statistics.

[a] Dependent variable is change in return on equity from t to $t+1$ $(R_{i,t+1} - R_{i,t})$.

[b] $R_{i,t} - E(R_{i,t})$ is the deviation of the rate of return on equity from the individual mean.

[c] $E(R_{i,t}) - E(R_t)$ is the deviation of the individual mean from the global mean.

[d] $R_{i,t} - R_{i,t-1}$ is the change in the rate of return on equity from $t-1$ to t.

Alternative definitions of profitability are also possible. So far, we have defined profitability as return on assets. When profitability is defined as return on equity, the results from the partial adjustment model change (Table 4). Both mean reversion and autocorrelation of profitability become insignificant.

A further look into the decomposition of return on assets and return on equity can help explain these results. According to the DuPont System equations, return on assets can be decomposed into an efficiency ratio (sales-to-asset ratio) and a profitability ratio (net profit margin). Further, return on equity can be obtained by multiplying the return on assets, the asset-to-equity (leverage) ratio, and a term including the interest expense associated with debt. Thus, the results show that when our measure of profitability—return on assets—includes only the efficiency and profitability ratios, profitability is mean-reverting and autocorrelated. However, when leverage and interest expenses are

Table 5. Regression Results for the Partial Adjustment Models by Groups

	By Age Groups		By Credit Risk Groups	
Variable [a]	**Younger Farmers** [b]	**Older Farmers** [c]	**Low Credit Risk Farms** [d]	**High Credit Risk Farms** [e]
Intercept	-0.004	-0.002	-0.003	-0.001
	(-0.27)	(-0.14)	(-0.31)	(-0.14)
$R_{i,t} - E(R_{i,t})$ [f]	-0.517	-0.460***	-0.328	-0.461
	(-1.22)	(-3.06)	(-0.68)	(-1.40)
$E(R_{i,t}) - E(R_t)$ [g]	-0.460*	-0.390**	-0.291	-0.475*
	(-1.68)	(-2.13)	(-0.86)	(-1.84)
$R_{i,t} - R_{i,t-1}$ [h]	-0.212	-0.244*	-0.337	-0.158
	(-1.25)	(-1.95)	(-1.40)	(-0.63)
Adjusted R^2	0.41	0.34	0.38	0.33
Number of Observations	2,909	3,253	1,704	1,011

Notes: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed *t*-test. Coefficients are averaged from cross-sectional regressions for 1986–2001. Numbers in parentheses are *t*-statistics.

[a] Dependent variable is change in return on assets from t to $t+1$ $(R_{i,t+1} - R_{i,t})$.

[b] Younger farmers are 40 years of age or younger.

[c] Older farmers are 55 years of age or older.

[d] The low credit risk group includes farms with a credit score lower than 1.6.

[e] The high credit risk group includes farms with a credit score greater than 3.3

[f] $R_{i,t} - E(R_{i,t})$ is the deviation of the rate of return on assets from the individual mean.

[g] $E(R_{i,t}) - E(R_t)$ is the deviation of the individual mean from the global mean.

[h] $R_{i,t} - R_{i,t-1}$ is the change in the rate of return on assets from $t-1$ to t.

also taken into account, they tend to neutralize the effects of the efficiency and profitability ratios, whereby return on equity is no longer mean-reverting and autocorrelated.

Results of Comparison Between Age Groups

To further explain differences in the rate of mean reversion of profitability, OLS regressions are performed for partial adjustment model (1) for each of the two age samples (40 years of age or younger and 55 years of age or older). Mean coefficients and *t*-statistics are calculated, and results are presented in Table 5.[6] Two separate expected profitability models are estimated for younger and older farmers. The results for the naïve model for expected profitability show that the global mean profitability is 0.032 for younger farmers and 0.027 for older farmers.

Results suggest that the rate of mean reversion toward an individual farm level differs slightly between age groups. For older farmers, the rate of mean reversion is 0.46, while the autocorrelation in farm profitability is 0.244, and both coefficients are statistically significant. Mean reversion and autocorrelation for younger farmers are 0.517 and 0.212, respectively, but these coefficients are not significant. Comparisons between these two sets of coefficients for old and young farmers reveal that mean reversion and autocorrelation rates do not differ significantly based on farmers' age.

These general results are contrary to our hypothesis—i.e., older farmers, who are assumed to have accumulated more experience and resources than younger farmers, were expected to adjust more slowly to long-run levels of profitability

[6] For the regressions by age group and credit risk group, only the full models are reported here.

than younger farmers. However, the results indicate similar speed of adjustment for older and younger farmers. This finding may also be related to the quasi-fixity of human capital (Mishra, Moss, and Erickson, 2004).

Results of Comparison Between Credit Risk Groups

Differences in the rate of mean reversion of profitability are explored for the two credit risk groups, and these results are also reported in Table 5. Separate expected profitability models are estimated for farms with low credit risk (a credit score lower than 1.6) and for those with high credit risk (a credit score greater than 3.3). The naïve models for expected profitability predict that the global mean profitability is 0.038 for farms with low credit risk and 0.016 for farms with high credit risk.

The rate of mean reversion is 0.328 for farms with low credit risk and 0.461 for farms with high credit risk, but neither of these coefficients is significant. The autocorrelation rate for low credit risk farms is 0.337 and for high credit risk farms is 0.158, but once again these coefficients are not significantly different than zero. Further *t*-tests confirm that the mean reversion and autocorrelation rates do not differ significantly based on farm credit risk.

Farms with low credit risk are generally assumed to be less financially constrained. Consequently, credit risk may proxy other characteristics such as leverage and operator age or risk aversion. Based on the results found here, these less financially constrained farms are able to adjust to long-run levels of profitability at the same rate as more financially constrained farms. Overall, our findings show that the rates of mean reversion and autocorrelation are similar across credit risk groups.

Conclusions

The objective of this study was to estimate rates of mean reversion and autocorrelation in farm profitability. The existing agricultural economics literature was extended by applying a partial adjustment model to Illinois farm businesses to determine the rates of mean reversion and autocorrelation in farm profitability. Our results suggest that the predictable variation in profitability of farms can be attributed to both mean reversion and negative autocorrelation.

When all farms are assumed to revert toward an individual level of expected profitability, the rate of mean reversion is 0.497, with a rate of negative autocorrelation of 0.175. When our results are compared to those of Fama and French (2000), the farm businesses in our sample experience higher rates of mean reversion and negative autocorrelation than other types of businesses. After testing and imposing the appropriate coefficient restrictions, the results show that farm profitability mean reverts toward an industry-wide level at an annual rate of 0.5. The similarity between these two rates of mean reversion suggests individual expected profitability may not explain as much of the variation in the profitability of farm businesses as it does for other types of businesses.

In addition, we estimate rates of mean reversion and negative autocorrelation across farmer age groups and credit risk groups. Mean reversion and autocorrelation rates were not found to differ significantly across these groups.

Farm profitability is of great interest to a diverse group of people, including farmers, input providers, output users, agricultural lenders, government agencies, and policy makers. Changes in farm policies, particularly decreases in federal subsidies, may potentially increase the variability of farm profitability, which could have a significant impact on the farm sector.

While a great deal of research has been conducted on the variables influencing farm profitability, dissection of the driving forces behind fluctuations in farm

profitability, such as mean reversion and autocorrelation, is also needed to more accurately predict long-term farm profitability. Further analysis of distributions of profitability across farm and operator attributes, such as operator age and credit risk, may also result in better predictions and more realistic models of long-term farm profitability.

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