The Structure Model Based Determinants of Capital Structure: A Seemingly Unrelated Regression Model

Yan Yan, Xiangdong Shi, Peter Barry, Nicholas Paulson, Bruce Sherrick

Contact Author

Yan Yan
University of Illinois at Urbana-Champaign
Department of Agricultural and Consumer Economics
1301 West Gregory Drive
Urbana, IL 61801
Tel: (952) 457-5994
Email: yanyan@uiuc.edu

Yan Yan is a PhD student, Peter J. Barry is a Professor, Nicholas Paulson is an Assistant Professor, and Bruce Sherrick is a Professor at Department of Agricultural and Consumer Economics at the University of Illinois at Urbana-Champaign. Xiangdong Shi is a PhD student at Department of Applied Economics at the University of Minnesota at Twin Cities.

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Abstract:

This study proposed a seemingly unrelated regression model to investigate the predicting capability of the structure model and test the capital structure theories. The model considered dynamic property of the structure model and characteristics of farm records. FBFM data are used in empirical analysis. The regression results provide new supportive evidence on capital theories.

Keyword: Structure Model, Capital Structure, Seemingly Unrelated Regression

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Introduction

The structure model (Merton, 1974) is widely used for predicting firm financial performance by transforming asset value into leverage ratio (Longstaff and Schwartz, Black and Cox, Leland, Leland and Toft, Crouhy and Galai, and more). Proponents of the model state that the structure model "provides a rigorous, internally consistent framework from which we can draw economically meaningful inferences. Because the parameters that characterize structural models have economic interpretations, they lend themselves to scrutiny on theoretical as well as empirical grounds." And compared to multivariate factor models, "models with fewer parameters are generally more easily identified by available data, and model their parameters can be estimated more efficiently. Highly parameterized models have a tendency to "over-fit" observed data, reducing the effectiveness of out- of-sample forecasts" (Gordy et al).

While theoretical elegant, there are some problems for its empirical application. For example, in the case of measuring credit risk, the model turns to "produces probabilities that are unrealistic in practice" (Stein). Therefore, modeling of joint default and prediction accuracy as compared to historical default rates captures more and more concerns (Altman Barry, Stein, Gordy et al, Frey and McNeil, Crouhy et al, Bouyé et al, Boyer et al, and more). A recent study using KMV model to farm records also confirms the problem (Katchova and Barry). As for the reason, Ericsson et al stated that the under-prediction seems mainly due to factors not included in the structure models rather than the prediction capability, while Caouette et al pointed out "by narrowing down the range of possible variables and types of interactions… there is possibility of under-fitting (excluding what may be an important

variable)". In this sense, an econometric multi-factor model based on the structure model should be a better choice for proper fitting.

The structural model addresses the choice of financial structure by the firm, which is determined by assets return and its volatility. Whether there exists such specific association between response and predictor remains to be checked empirically. In practice, determinants of a firm's capital structures have long been an important field in corporate finance. There are many theories, in contrast to the structure model, describing the determinants of capital structure, such as the oldest trade-off theory, pecking order theory (Myers and Majluf), signaling theory (Ross), and agency theory (Jensen). These theories coupled with the structure model are associated with assets return and volatility, firm size, profitability, non-debt tax shield, tenure position and risk tolerance, which provide possible choice of variables in an econometric model.

Of the studies on empirically testing the theories on capital structure, most of them are focused on public firms (Titman and Wessels, Altman, Myers, Vogt and more), with few on non-public firms (Schoubben and Hulle, Barry et al). As for farm capital structure, past studies mainly support the pecking order theory and trade-off theory (Barry et al). In addition, the studies on non-public firms revealed that the determinants of capital structure differ to some extent between the public and non-public firms. Thus, study of farm capital structure may provide further proof for this observation. On the other hand, it also reminds the reader that farm characteristics must be taken into account carefully when farm record is used to the structure model as it does in this paper.

Under the structure model, the measurement of firm financial performance generally relies on the joint normality of the latent variables, i.e. assets return, which is implied by firm financial data. In the case of credit risk measurement, Crouhy et al pointed out that even in a simple bi-variate case, "the joint probability of default is in fact quite sensitive to pair-wise

asset return correlations, and (this) illustrates the necessity to estimate correctly these (sample) data to assess precisely the diversification effect within a portfolio". Of the econometric models, the dependence structure can be captured by seemingly unrelated regression model (SUR). The model is a system of linear equations that are linked through the correlations among the errors, and has been used in studies of financial market (Campbell et al). When covariance matrix of disturbance is unknown, feasible generalized least square method (FGLS) can be applied to get the parameters and correlation coefficients simultaneously (Zellner, Zellner and Huang), while "the least squares residuals may be used (of course) to estimate consistently the elements of covariance matrix of disturbance" (Greene).

This paper tries to find a proper econometric multi-factor model describing the choice of capital structure on the basis of the structure model. For the purpose, the property of the structure model and characteristics of farm records used in this study will be investigated at first, and seemingly unrelated regression model and three stages least square procedure will be then proposed to get proper estimates. The possible predictors associated with capital structure will be determined in terms of the structure model and capital theories, while log likelihood ratio test will be applied for model selection. The selected model and estimates will be given. On the basis, the prediction capability of the structure model will be checked while testing result on capital theories in explaining the farm financial structure will be discussed.

Structure Model Based Financial Performance

Under the framework of Merton's model, the value of farm assets A_t at time t is assumed to follow a standard geometric Brownian motion

1) $$A_t = A_0 \exp((\mu - \frac{\sigma^2}{2})t + \sigma\sqrt{t}\omega_t))$$

where A_0 is the initial assets value, μ is the instantaneous expected rate of return (growth), σ is the standard deviation of the return on the underlying assets (risk), and ω_t is a standard normal variable with mean zero and variance 1.

By proper transforming, the model can be written as

2) $$\ln A_t = \ln A_{t-1} + (\mu - \frac{\sigma^2}{2}) + \sigma(\sqrt{t}\omega_t - \sqrt{t-1}\omega_{t-1})$$

where the random term $\sigma(\sqrt{t}\omega_t - \sqrt{t-1}\omega_{t-1})$, denoted as ε_t, is normally distributed with mean zero and variance (2t-1)σ^2. When farm financial performance is described by the leverage position, i.e. $\frac{A_t}{D_t}$, where D_t is debt value at time t, subtracting $\ln D_t$ from both sides of equation (2) yields

3) $$\ln \frac{A_t}{D_t} = \ln \frac{A_{t-1}}{D_t} + (\mu - \frac{\sigma^2}{2}) + \varepsilon_t$$

Now, if we define $y_t = \ln \frac{A_t}{D_t}$ and $y_{t-1} = \ln \frac{A_{t-1}}{D_t}$, then expression (3) can be easily expressed as a linear regression model

4) $$\begin{aligned} y_t &= \beta_0 + \beta_1 y_{t-1} + \beta_2 \mu + \beta_3 \sigma^2 + \varepsilon_t \\ &= x'\beta + \varepsilon_t \end{aligned}$$

where x is the vector of independent variables and $x = (y_{t-1}, \mu, \sigma^2)'$, β are the vector of parameters to be estimated, and ε_t ~N(0, (2t-1)σ^2). In the model, log of assets to debt ratio, a measurement of farm's leverage position, is the dependent variable that represents an underlying farm's choice of capital structure and is determined by farm characteristics.

In equilibrium when $t, t-1 = e$, the equilibrium leverage position can be further investigated by equation (5) as

5) $$y_e = \frac{\beta_0}{1-\beta_1} + \frac{\beta_2\mu + \beta_3\sigma^2}{1-\beta_1} + \frac{\varepsilon_e}{1-\beta_1}$$

A major concern about empirical application of the model is that the observed farm financial performance may be associated with each other, and this kind of dependence is often true in reality (Barry). On the other hand, when there are non-spherical disturbances in a linear regression model, OLS estimator will be inefficient although still unbiased and consistent, but the standard error of the estimator is biased and inconsistent. Therefore, a proper linear regression model and corresponding estimation procedure are needed to address the problem.

Seemingly Unrelated Regression Model When Correlation Matrix is Unknown

In econometrics, seemingly unrelated regression (SUR) is a technique for analyzing a system of multiple equations with cross-equation parameter restrictions and correlated error terms. Given the econometric model for farm finanical performance, it is possible to get the parameters and correlation coefficients simultaneously with feasible generalized least square method (FGLS) (Zellner, Zellner and Huang).

Following Greene, a seemingly unrelated regressions (SUR) model can be written as

6) $$y_k = X_k\beta_k + \varepsilon_k \qquad k = 1,\cdots,M$$

where y is vector of dependent variables, X is $K \times K$ matrix, K is number of regressors, and M is the number of equations, the assumption about the error vector $\varepsilon = \left[\varepsilon_{1,}'\varepsilon_{2,}'\cdots,\varepsilon_M'\right]$ is then

7) $$\begin{aligned} &E\left[\varepsilon \mid X_1, X_2, \cdots, X_M\right] = 0 \\ &E\left[\varepsilon\varepsilon' \mid X_1, X_2, \cdots, X_M\right] = \Omega \qquad \Omega = \Sigma \otimes I \end{aligned}$$

where Σ is variance and covariance matrix. The stacked model with respect to expression 6) is then written as followings.

8) $$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_M \end{bmatrix} = \begin{bmatrix} X_1 & 0 & \cdots & 0 \\ 0 & X_2 & \cdots & 0 \\ & \vdots & \vdots & \\ 0 & 0 & \ddots & X_M \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_M \end{bmatrix} + \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_M \end{bmatrix} = X\beta + \varepsilon$$

The efficient estimator can be obtained by generalized least squares (GLS) regression given the covariance matrix of the disturbance. For the $t-th$ observation, the $M \times M$ covariance matrix of the disturbance is

9) $$\Sigma = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \cdots & \sigma_{1M} \\ \sigma_{21} & \sigma_{22} & \cdots & \sigma_{2M} \\ & \vdots & \vdots & \\ \sigma_{M1} & \sigma_{M2} & \ddots & \sigma_{MM} \end{bmatrix}$$

with $\Omega^{-1} = \Sigma^{-1} \otimes I$. If a total of T observations are used in estimating the parameters of the M equations, then we require $T > K$. When the error term are correlated, "the lease square residuals may be used to (of course) estimate consistently the elements (covariance items) of Σ" (Greene), which equals to

10) $$\hat{s}_{jk} = \frac{e_j' e_k}{T} \qquad \text{j, k} = 1, \ldots\ldots, \text{M}$$

For a known covariance matrix, the GLS estimator is given as following

11) $$\hat{\beta} = \left[X'\Omega^{-1}X\right]^{-1} X'\Omega^{-1} y = \left[X'(\Sigma^{-1} \otimes I)X\right]^{-1} X'(\Sigma^{-1} \otimes I)y$$

Since farm records are often characterized by short time periods and large number of farms, model for panel data have to be applied to groups of farms to increase the degree of freedom in SUR. For the purpose, farms are first grouped in terms of similarity, with each equation in SUR describing each farm group. By assuming that farms in the same group are identical, the observations in the group can be treated as a sample derived independently from the same population.

Another major concern is that the structure model is dynamic. When using dynamic panel data model, since the lagged dependent variable is correlated with the disturbance, the within estimator is biased given small and fixed time period, and large cross-section sample size (Nickell). To address the problem, the paper applied a specific three stage least square estimations to the SUR model, in which the instrumental variables based semi-parametric procedure is applied first to data transformation. For consistence with SUR model, the paper specifically focuses on the "feasible" instrumental variable OLS estimator that "can be obtained by replacing the unknown conditional mean functions by some nonparametric estimators, say the nonparametric kernel estimators." (Baltagi and Li).

Determinants of Capital Structure: Theory and Evidence

This section pays attention to possible variables implied by the capital structure theories besides those in the structure model. Actually, determinants of a firm's capital structures have long been an important area in corporate finance since Miller and Modigliani's pioneer work in 1958. Of a firm's choice of capital structure, the trade-off theory is the oldest one, which indicates that a firm optimizes its debt level such that marginal tax advantage of additional borrowing is offset by the increase in the cost of financial difficulties. The followed pecking order theory says that firms prefer to finance their investments from internally generated cash flowing as their first best choice as compared to borrowing (Myers and Majluf). Two other theories related to asymmetric information are signaling theory (Ross) and agency theory (Jensen). Signaling theory suggests that investors interpret higher levels of debt as a signal of higher credit quality and higher future cash flows. Due to the high expected costs of financial distress at any debt level, lower credit firms cannot mimic higher credit firms by taking on more debt. According to agency theory, the potential conflict of interests between management and shareholders in a company may lead to either under investment or over

investment. Most of the empirically testing on the theories worked on public firms (Titman and Wessels, Altman, Myers, Vogt and more), with few on non-public firms (Schoubben and Hulle, Barry et al). A recent study on farm capital structure supports the pecking order theory as well as the trade off theory (Barry et al, 2000).

In the paper, we consider several variables that may have potential impact on farm's choice of capital structure, including farm size, growth potential, profitability, collateral position, tenure and non-tax shield. Farm size is represented by log of farm cash sale (Size). Since farm business is typically small in size, and has limited access to equity market due to asymmetric information. In light of pecking order, signaling and agency theories, farms would tend to be more relied on debt financing as their sale increases. The average return per unite risk taken (CV) describes a farm's growth potential. Because internal financing is not likely to fill the needs of these firms, the pecking order theory would predict that growing farms are likely to hold more debt. However, due to the increase cost of bankruptcy and asymmetric information, the other three theories suggest the opposite.

Two variables are selected to describe farm profitability or potential cash flow, the ratio of farm's earning before interest and tax over farm cash sale (EBIT/Sale) and log of farm cash sale to total debt ratio (sale/debt). In light of pecking order theory that farms prefer financing through retained earnings first before moving to debt, farms with high profitability and hence high opportunities to retain earning should have lower debt. Moreover, as strong cash flow may serve as an alterative signal of quality, there is no need for these farms to distinguish themselves from lower quality farms by taking on more debt. As contrast, trade-off theory suggests that high profitability farms are less likely to go bankruptcy, and thus can sustain more debt, while agency theory predicts that the need to refrain manager from engaging in a sub optimal investment project would lead to a negative relationship between profitability and debt level.

Collateral position is measured by value of farmland plus machinery and equipment to total asset (Collateral Ratio). Since tenure is measured as the owned land to total tillable land ratio, it is closely associated with the collateral ratio. A farm with large portion of owned land is expected to have a relative higher collateral ratio. Since higher liquidation value for farms with a relatively large portion of tangible assets would reduce the bankruptcy costs while there exists clearly cost effective of issuing secured debt for farms with assets that can be collateralized, both pecking order theory and trade off theory suggest a positive relationship between the two variables with the debt level. The final variable considered here is the non-debt tax shield (shield), which is measured by depreciation over total assets. It is reasonable to say that for a farm with large non-debt tax shield should also have considerable tangible assets. It has opposite effect on the debt to assets ratio as suggested by trade-off theory.

Considering the cycle of farm production, current debt to current assets ratio (composite) is also involved in the model. Given this, the full system of equations is then

$$12)\quad \begin{aligned} \ln\left(\frac{assets}{debt}\right)_{kt} &= \alpha_{kt} + \beta_{k1}\ln\left(\frac{assets}{debt}\right)_{kt-1} + \beta_{k2}CV_{kt} + \beta_{k3}composite_{kt} + \beta_{k4}size_{kt} + \beta_{k5}\left(\frac{EBIT}{Sale}\right)_{kt} \\ &\quad + \beta_{k6}(colateral\quad ratio)_{kt} + \beta_{i7}shield_{kt} + \beta_{k8}tenure_{kt} + \beta_{k9}\ln\left(\frac{sale}{debt}\right)_{kt} + \varepsilon_{kt} \end{aligned}$$

for $k = 1,\cdots,M$ and $t = 1,\cdots,T$, where M and T denote number of equations or number of farm groups and time period respectively.

Data and Summary Statistics

The study uses the annual farm data from 1995 through 2004 provided by Farm Business Farm Management Association (FBFM). It contains farm accounting information, such as income and cash flow statement, as well as farm reported market value on assets and liabilities. Since longer time range of data is better for revealing assets volatilities and choice

of capital structure, included in the study are farm records with a maximum time range of 10 years. For computing leverage ratio, farms with no debt are excluded from the dataset, which results in 4372 farm observations with 635 farms. Basic statistics for selected variables and distribution of selected variable means by total debt to assets ratio (capital structure) is listed in table 1 and table 2 respectively.

Table 1 Basic Statistics for the Selected Variables of FBFM Farms (1996-2004)

Variable	Description	Mean	Median	Standare Deviation
Log (assets/debt)	Log of total assets to total debt	1.38	1.20	0.80
Log (lag of assets to debt ratio)	Log of lag value of total assets to total debt	1.33	1.16	0.74
Composite	Current debt to current assets ratio	0.69	0.65	0.46
Size	Log of farm cash sale	12.34	12.36	0.54
CV	Return on assets to its volatility	0.44	0.25	0.83
Tenure	Owned land to total tillable land	0.19	0.12	0.21
Log(sale/debt)	Log of farm cash sale to total debt ratio	-0.09	-0.21	0.72
Age	Age	50.13	49.56	9.31
Collateral ratio	assets	0.54	0.56	0.16
Shield	Depreciation to total assets	0.006	0.004	0.007
EBIT/Sale	EBIT to farm cash sale	0.39	0.39	0.16

Table 2 illustrates a clear pattern of decreasing in tenure, age, CV, collateral ratio, and profitability as ratio of debt to assets increases on average, while the current debt to current assets ratio (composite) and size move in the same direction as debt to assets ratio increases. The farm group with assets value less than total liabilities on average has the lowest average return per unite risk taken (CV) (0.095), the lowest profitability (0.29) but the highest composite (1.36) as compared to other farm groups and the average farm (table 1). These farms are largely composed of younger leasing farms, and have higher scale than average. Most of their debt could be non-collateralized as implied by the lowest collateral ratio (45.4%) in the group, and these farms are likely to take advantage of non-tax shield (0.0076). Noted that it is unclear whether the group covers failing farms although the group is characteristic by assets value less than total liabilities.

Table 2 Distribution of Selected Variable Means by Debt to Assets Ratio

Variables	Composite	Size	CV	Tenure	Log(sale/debt)	Age	Collateral ratio	Shield	EBIT/Sale	Farm Obs.
D/A <= 0.2	0.297	12.23	0.4672	0.256	0.589	53.85	0.541	0.00318	0.427	1395
0.2< D/A <=0.25	0.560	12.25	0.4622	0.226	-0.134	51.19	0.551	0.00645	0.420	470
0.25< D/A < 0.3	0.636	12.35	0.4743	0.191	-0.247	50.17	0.556	0.00681	0.413	466
0.3 < D/A <=0.35	0.736	12.34	0.4298	0.166	-0.317	48.23	0.554	0.00654	0.397	462
0.35 < D/A <=0.4	0.851	12.32	0.4186	0.161	-0.395	48.38	0.543	0.00686	0.374	392
0.4 < D/A <=0.5	0.938	12.43	0.433	0.134	-0.469	47.31	0.542	0.00694	0.370	650
0.5< D/A <=0.6	1.048	12.49	0.4802	0.127	-0.536	46.70	0.526	0.00759	0.348	446
0.6< D/A < 0.7	1.186	12.46	0.3274	0.105	-0.619	48.17	0.529	0.00764	0.320	269
0.7 < D/A <=0.8	1.255	12.40	0.1734	0.062	-0.511	48.12	0.479	0.00653	0.324	86
D/A > 0.8	1.360	12.64	0.0954	0.062	-0.482	47.26	0.454	0.00759	0.290	36

D/A = total debt to total assets

Estimation and Inference

Since some of farm records have missing values within the 10 years period, multiple imputation technique is used to get the complete-data. The method was first introduced by Rubin (1987) to incorporate missing-data uncertainty, and has been widely used in survey data analysis (Schafer, Schafer and Schenker, Reilly, Rubin, Li, and more). Rubin pointed out that when missing rate are low, highly efficient inference can be achieved with only a few imputations. Schafer and Schenker illustrated that multiple imputation "shows good coverage at all rates of missingness, even with only M=5 imputations". For the sample data we consider here, since the missing rate is about 16% percent, multiple imputation with number of imputations equal to 5 is used, and missing values are replaced by average imputed values. The following empirical analysis is then based on the complete dataset.

The farms are grouped by three splits methods, that is, first by assets value of each farm, then by age of farmer, and third by application of a credit-scoring model (Barry et. al 2004). The groupings are with respect to the values for the year (1995) prior to 1996-2004 estimation periods. Each of the groupings will divide the farms into 10 groups, each reflecting 10% quintile of the sample population based on split variables. Accordingly, the SUR model consists of a system of 10 equations, each of which describes a farm group.

Empirical estimation then applies the specific three stage least square estimation based on the semi-parametric procedure (Baltagi and Li). In the light of the procedure, the semi-parametric dynamic panel model based on equation (12) can be written as

13) $$y_{it} = x'_{it}\beta + \theta(z_{it}) + u_{it} \qquad \text{for } i = 1,\cdots,N;\ t = 1\cdots,T$$

where

$y_{it} = \ln(\frac{assets}{debt})_{it}$, and

$$x_{it} = \left(\ln(\frac{assets}{debt})_{it-1}, CV_{it}, composite_{it}, size_{it}, (\frac{EBIT}{sale})_{it}, (colaterail \quad ratio)_{it,} shield_{it}, tenure_{it}, \ln(\frac{sale}{debt})_{it} \right)',$$

z_{it} is a vector of selected variable that is weakly exogenous in the sense that $E(u_{it} \mid z_{is}) = 0$ for s≤t, and $\theta(.)$ is smooth function.

The independent variables can be further split into two parts as $x_{it} = (x'_{1.it}, x'_{2,it})'$, where $x_{1,it}$ is the vector of endogenous variables, and $x_{2,it}$ is the vector of exogenous variables. The vector of instrumental variables is then equal to $w_{it} = (w'_{1.it}, w'_{2,it})'$, with $w_{1.it} = E(x_{1,it} \mid z_{2,it-1})$ and $w_{2.it} = x_{2,it}$. The conditional expectations of $y_{it,}$, $x_{it,}$ and w_{it} given z_{it} are estimated by the kernel function (Robinson). Given the estimates $\hat{y}_{it,}$, $\hat{x}_{it,}$ and $\hat{w}_{it}$, and define $\tilde{v}_f = \hat{v}_{it} - \sum_{s=1}^{T} \hat{v}_{it}$ with $\hat{v}_{it} = x_{it} - \sum_{s=1}^{T} \hat{x}_{it}$, $\tilde{w}_f = \hat{w}_{it} - \sum_{s=1}^{T} \hat{w}_{it}$ with $\hat{w}_{it} = w_{it} - \sum_{s=1}^{T} \hat{w}_{it}$, and $\tilde{y} = y_{it} - \sum_{s=1}^{T} y_{it}$ with $\tilde{\zeta}_{it} = \hat{y}_{it} - \sum_{s=1}^{T} \hat{y}_{it}$, the feasible within estimates of the parameters β is then

14) $$\hat{\beta} = (\tilde{v}'_f \tilde{w}_f \tilde{w}'_f \tilde{v}_f)^{-1} \tilde{v}'_f \tilde{w}_f \tilde{w}'_f (\tilde{y} - \tilde{\varsigma}_f)$$

In the paper, the lag value of assets to debt ratio is treated as endogenous, while lag values of composite, size, log of sale to debt ratio and tenure are used to create the instrumental variable for the endogenous variable. Given this, log likelihood ratio test for the hierarchically nested models are used to determine the final variables that enters the final

model. The final variables that enter the model include lag value of assets to debt ratio, composite, size, tenure, CV and log of sale to debt ratio. The final model is

14)

$$\ln(\frac{assets_{it}}{debt_{it}}) = \beta_{i1}\ln(\frac{assets_{it-1}}{debt_{it-1}}) + \beta_{i2}cv_{it} + \beta_{i3}size_{it} + \beta_{i4}composite + \beta_{i5}tenure_{it} + \beta_{i6}\ln(\frac{sale_{it}}{debt_{it}}) + u_{it}$$

$$\text{for} \quad i = 1, \cdots, N; \; t = 1 \cdots, T$$

The regression results for assets value split are listed in table 3. Except for the coefficient for the lag of assets to debt ratio, all coefficients are statistically significant at better than the conventional level of 5%. The stability of the dynamic system is checked by the procedure of stability test (Greene). Since the absolute values of the coefficients corresponding to lag value of assets to debt ratio are less than one, we conclude that the system is stable. By checking the results, we can find that, (1) the coefficients for the lag value of assets to debt ratio are negative for the equations, and are significant for seven equations. The results are consistent with the trade off theory, which indicates that farms appear to adjust to long run financial targets; (2) Farm size is negative to the log of assets to debt ratio, as predicted by pecking order theory, as well as agency and signaling perspectives. It contradicts, however, the trade off theory; (3) The positive and significant relationship between tenure and log asset to debt ratio suggests that farms increase their debt targets as their leasing targets increases, which is consistent with the trade off theory; (4) CV is significantly positive to the log assets to debt ratio. The result contradicts the pecking order theory but is in line with the other three theories on capital structure as mentioned; (5) The log of sale to debt coefficient is significantly positive, consistent with pecking order theory and agency perspective on capital structure.

The results by applying the age and credit score model split are listed in table 3 and table 4, which are similar to that by asset split. Overall, the results on average support both

pecking order theory and trade off theory, which is consistent with previous studies, while it provides new supportive evidence on the agency theory. The positive relationship between CV and log assets to debt ratio also confirms previous studies on risk balancing (Escalante and Barry, Yan et al.).

Table 3 1996-2004 Estimation Results for the Seeming Unrelated Regression Model by Operator Assets Splits

Variable \ Group	Group1	Group2	Group3	Group4	Group5	Group6	Group7	Group8	Group9	Group10
Log (lag of assets to debt ratio)	-0.117**	-0.165*	-0.357***	-0.089	-0.157*	-0.017	-0.141*	-0.082***	-0.121**	-0.013
	(0.05)	(0.04)	(0.23)	(0.07)	(0.04)	(0.02)	(0.03)	(0.04)	(0.05)	(0.03)
Composite	-0.084**	-0.122*	-0.094*	-0.099*	-0.079*	-0.021	-0.075*	-0.021	-0.152*	-0.177*
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)
Size	-0.267*	-0.292*	-0.435*	-0.321*	-0.421*	-0.537*	-0.494*	-0.511*	-0.548*	-0.585*
	(0.03)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)
CV	0.036*	0.0318*	0.0291*	0.025*	0.029*	0.041*	0.025*	0.035*	0.041*	0.039*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.01)	(0.01)
Tenure	0.954*	0.508*	0.211***	0.387*	0.421*	0.138*	0.315*	0.355*	0.516*	0.453*
	(0.10)	(0.07)	(0.11)	(0.07)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
Log(sale/debt)	0.427*	0.416*	0.511*	0.489*	0.544*	0.716*	0.667*	0.625*	0.716*	0.736*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.02)
R-square	0.6868									

Note: single, double and triple asterisks (*) denote significance at 1%, 5% and 10% confidence level respectively

Table 4 1996-2004 Estimation Results for the Seeming Unrelated Regression Model by Operator Age Splits

Variable \ Group	Group1	Group2	Group3	Group4	Group5	Group6	Group7	Group8	Group9	Group10
Log (lag of assets to debt ratio)	-0.072	-0.124*	-0.1165*	-0.042	-0.115*	-0.051	-0.074	-0.087**	-0.039	-0.061
	(0.05)	(0.05)	(0.04)	(0.03)	(0.03)	(0.04)	(0.22)	(0.04)	(0.03)	(0.08)
Composite	-0.102*	-0.091*	-0.055**	-0.117*	-0.169*	-0.101*	-0.106*	-0.261*	-0.101*	-0.099*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.04)
Size	-0.137*	-0.232*	-0.258*	-0.266*	-0.257*	-0.232*	-0.343*	-0.22*	-0.385*	-0.524*
	(0.02)	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.03)	(0.03)
CV	0.023*	0.036*	0.048*	0.038*	0.036*	0.041*	0.034*	0.036*	0.0471*	0.056*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Tenure	0.489*	0.529*	0.527*	0.848*	0.581*	0.964*	0.943*	0.785*	0.844*	0.385*
	(0.05)	(0.08)	(0.08)	(0.10)	(0.09)	(0.07)	(0.08)	(0.07)	(0.06)	(0.06)
Log(sale/debt)	0.293*	0.482*	0.441*	0.494*	0.515*	0.539*	0.674*	0.511*	0.651*	0.726*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
R-square	0.6012									

Note: single, double and triple asterisks (*) denote significance at 1%, 5% and 10% confidence level respectively

Table 5 1996-2004 Estimation Results for the Seeming Unrelated Regression Model by Operator Credit Score Splits

Variable \ Group	Group1	Group2	Group3	Group4	Group5	Group6	Group7	Group8	Group9	Group10
Log (lag of assets to debt ratio)	0.091***	-0.224*	0.090	-0.011	0.023	-0.038	0.568	0.282	-0.006	0.051
	(0.05)	(0.09)	(0.12)	(0.09)	(0.14)	(0.22)	(0.43)	(1.17)	(0.20)	(0.39)
Composite	-0.222*	-0.015	-0.059	-0.102*	-0.005	-0.06**	-0.036	-0.051*	-0.031***	-0.042***
	(0.05)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)
Size	-0.229*	-0.379*	-0.239*	-0.205*	-0.176*	-0.18*	-0.199*	-0.123*	-0.092*	-0.097*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
CV	0.045*	0.047*	0.042*	0.022*	0.022*	0.021*	0.034*	0.016**	0.011*	0.026*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Tenure	0.815*	0.454*	0.774*	0.253*	0.709*	0.359*	0.471*	0.468*	0.328*	0.242*
	(0.06)	(0.07)	(0.07)	(0.07)	(0.08)	(0.06)	(0.05)	(0.06)	(0.05)	(0.08)
Log(sale/debt)	0.658*	0.635*	0.611*	0.441*	0.304*	0.337*	0.376*	0.262*	0.207*	0.13*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
R-square	0.5989									

Note: single, double and triple asterisks (*) denote significance at 1%, 5% and 10% confidence level respectively

Conclusion and Discussion

This study proposed an empirical model to investigate the predicting capability of the structure model and test the capital structure theories. The empirical model, seemingly unrelated regression model with panel data in each equation, considered dynamic property of the structure model and characteristics of farm records used in this paper, such as correlation over cross-section data as well as small and fixed time period coupled with large number of farms. A specific three stages least square is developed and applied for estimation. The statistic diagnostics for the model illustrated that the model is good for the data.

Model selection by LR test indicated that some other factors should be taken into account when we apply the structure model. The model gives chance to test capital structure theories. The regression results on average support both pecking order theory and trade off theory, which is consistent with previous studies, while it provides new supportive evidence on the agency theory. In long-term equilibrium, we can remove the lag asset to debt ratio by treating t and t-1 as the same. In the sense, static model is just a special case of the model. Since the coefficients for lag asset to debt ratio are negative, it is expected that all coefficients of other predictors would be larger in equilibrium.

By definition, a firm decides to default on its debt if its asset value falls below a sufficiently low level of its total debt. The constructed model dealing with the choice of capital structure can be used in credit risk measurement, such as estimation of correlation matrix and computing marginal distribution of farm financial performance. As mentioned before, a major concern in credit risk measurement is the modeling of joint default and prediction accuracy as compared to historical default rates. Since the model addresses the problems, its application will provide sound basis for credit risk measurement.

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