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Nonlinear Modeling of Target Leverage with Latent Determinant Variables - New Evidence on the Trade-off Theory

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Abstract

The trade-off theory on capital structure is tested by modelling the capital structure target as the solution to a maximization problem. This solution maps asset volatility and loss given default to optimal leverage. By applying nonlinear structural equation modelling, these unobservable variables are estimated based on observable indicator variables, and simultaneously, the speed of adjustment towards this leverage target is estimated. Linear specifications of the leverage target suffer from overlap between the predictions of various theories on capital structure about the sign and significance of determinants. In contrast, the framework applied here allows for a direct test: results confirm the trade-off theory for small and medium-sized firms, but not for large firms.

JEL: G32, G33, C61
Keywords: Capital Structure, Nonlinear, Latent Variables, Trade-off Theory

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1. Introduction

Explaining the level of and variation in corporate capital structure is the ongoing aim of a large body of empirical literature. Most commonly, linear regression - type models are applied to identify significant relationships between corporate characteristics and leverage. Independent variables are usually chosen among those that are related to company characteristics that, according to theory, exhibit a causal relationship to capital structure decisions. Among these theories is the trade-off-theory, which suggests that the optimal level of debt is reached just before the marginal tax advantage of debt is outweighed by the marginal cost of financial distress. Furthermore, agency benefits and cost of debt are suggested to play a role in determining corporate leverage, as well as market timing effects and information effects – such as signalling effects of the firm's choice between alternative sources of capital or the well-known pecking order theory. These theories provide causal relationships between corporate characteristics and leverage which can be used to form hypothesises on a relationship between company-specific observable variables and leverage, which themselves can easily be statistically tested by applying standard regression theory. However, it appears more difficult to directly test models of corporate capital. This is because first, the company-specific characteristics relevant for the theories cannot usually be perfectly measured. Second, the relationships between these characteristics and leverage are not necessarily linear. Third, the observable, current capital structure of companies differs from the optimal leverage due adjustment costs, market timing issues as well as exogenous shocks. And fourth, ex ante, the direction of the relationship between certain company characteristics and leverage is not unambiguous, due to contradictions between the causal relationships suggested by theory. It is difficult to find support for or to reject any of the theories, because empirical results often are consistent with more than one of them. This has the effect that a

considerable number of empirical studies concentrate on confirming significant determinant variables, rather than confirming theories. This study is an attempt to account for these difficulties and develops a model of the dynamics of corporate capital structure which is based on the maximization problem for company's wealth. It analyzes adjustments to corporate capital structure and explicitly models the capital structure target as a nonlinear function of company characteristics. There is a difference between searching for the nonlinear model that fits the data best and developing a nonlinear model based on a causal relationship between variables implied by corporate finance theory.

Here, the latter approach is taken by setting up the optimization problem for target leverage, based purely on the on the trade-off theory. Within that framework, the literature has developed model components that are robust enough to be applied to real world data. The relationships covered by the trade-off model are specified as follows: First, increasing leverage corresponds to a positive effect on firm value due to the tax shield, as long as the risk of default (and thus the risk of losing any tax advantage) does not outweigh this positive effect. Second, increasing leverage means, for a given level of business ("fundamental") risk, an increase in the probability of default and thus, an increase in the ex ante costs of financial distress resulting in a negative effect on firm value. The capital structure target is defined as that leverage where the marginal tax effect is just offset by the marginal distress costs effect. Company-specific variables relevant in this context are business risk and the amount of firm value lost in case of distress. To account for the unobservability of these characteristics, the concept of latent variables is applied and these are identified within a structural equation framework, based on a number of indicators for each characteristic. A simple approach is taken to model the trade-off: The tax shield is the expected net present value of all tax deductions induced by interest payments on debt, and the costs of financial distress are the expected net present value of losses of firm value that occur in the event of default. While

"initially", these losses are borne by the firm's creditors, they are indirectly borne by the company itself, because any stakeholder that enters into a contract with the firm will require an equivalent premium for bankruptcy risk. The expectation is taken over those states where the firm survives and those states where the firm defaults, and default probabilities are calculated within the framework of a structural model of credit risk which applies a jump-diffusion process for firm value and differentiates between systematic and non-systematic business risk. While this framework allows for a straight-forward implementation, it reflects only a part of the causal relationships prevalent in reality. Agency costs, information effects and transaction costs have received much less attention in the literature for a long time and comprehensive models are far from being close to reality.

The main contribution of the paper is to present a method that is capable of testing the trade-off model for (dynamic) capital structure choice directly and in isolation. Furthermore, it does provide a basis to incorporate any results from future research that allow an explicit specification of further value effects of leverage. From a methodological viewpoint, it contributes by applying the nonlinear structural equation framework, which combines the appealing idea of incorporating measurement error into the model itself and the flexibility of nonlinear modelling, into an econometric setting which, to our knowledge, has not yet been done before.

The rest of the paper is structured as follows. Section 2 briefly presents relevant results from the empirical literature on capital structure. Section 3 describes the model and its calibration and estimation, section 4 provides details on data sources and adjustments, section 5 presents and discusses the results, section 6 shows results of a goodness-of-fit comparison to a linear model, and section 7 concludes.

2. Capital Structure Theories and Empirical Tests

Commonly suggested theories on capital structure choice are presented in standard treatments of Corporate Finance, and are therefore not repeated here. Predictions implied by the trade-off theory have been partially confirmed not only in manager survey studies such as Graham and Harvey (2001), but also by studies focussing on company data such as Wald (1999) or Rajan and Zingales (1995), who themselves argue that it is difficult to interpret their evidence with regards to causal theory. In the following, due to the vast literature on capital structure choice, only a brief overview will be given on issues closely related to the aim of this paper. First, examples where different theories imply the same empirical pattern will be mentioned. Second, recent results on capital structure determinants and relevant methodological advances will be presented. According to Fama and French (2002), both an advanced version of the pecking order theory and the trade-off theory predict that firms with more investments will have less leverage. Baker and Wurgler (2002) find that firms are more likely to issue equity when their market to book ratio is low. However, a low market to book ratio could either indicate that the prospects of the firm have deteriorated and equity is issued to reduce insolvency risk, or indicate that the market underprices the firm's equity and equity is issued to benefit from this undervaluation. Myers (1977) shows that tangible assets are more likely to be financed by debt than intangible assets are. While on the hand, tangible assets could be considered less risky and therefore debt would have less of an impact on the insolvency risk, it was also argued that the underinvestment problem is less prevalent in firms with less growth opportunities and more tangible assets and thus that these firms would take on more debt. An adjustment model for capital structure has recently been applied by Antoniou, Guney and Paudyal (2008) who find that leverage is significantly influenced by the economic environment of the country in which a firm operates. Lemmons, Roberts and Zender (2008) find that much of the variation in leverage ratio levels is caused by an unobserved factor which is stable over long time intervals. De Jong, Kabir and Nguyen (2008) show that

country-specific factors not only determine the level of debt directly, but also influence the importance of firm-specific factors, which is confirmed by Lopez-Iturriaga and Rodriguez-Sanz (2008). Modelling company characteristics as latent variables to analyze capital structure determinants has previously been suggested by Titman and Wessels (1988) who use a linear structural equation model with 8 latent and 15 indicator variables. They find support for a number of theories suggested to explain capital structure decisions, but they cannot test these theories separately. Roberts (2002) has applied a state-space framework to capture measurement error of the determinants of a moving capital structure target. Pao and Chih (2005) found that artificial neural network methods increase the predictive power for Taiwanese high-tech companies' debt ratios, when compared to linear models. Fattouh, Harris and Scaramozzino (2008) capture nonlinearities in the relationship between determinants and leverage by dividing the sample into quantiles of the distribution of leverage and analyzing the linear regression coefficients for each quantile separately. That paper also presents a maximization model for the firm's optimal capital structure, which however does not focus on the quantification of marginal effects of debt, but which is rather presented to motivate the analysis of nonlinearities. Recently, Chang, Lee and Lee (2008) have applied linear structural equation modelling to capital structure choice.

3. Methodology

3.1. Adjustment-type Model for Corporate Capital Structure

Dynamic capital structure effects are accounted for using the adjustment model in (1). Here, optimal capital structure is assumed identical to the capital structure target, i.e. companies aim at adjusting towards the optimal capital structure over time. The change in capital structure from time t-1 to time t is assumed to consist of a drift towards the optimal capital structure associated to time t and of a random exogenous shock captured by the error term δ. The arguments of the l_t^* function will be explained in section 2.2.

$$l_t - l_{t-1} = \kappa(l_t^*(\sigma_{S,t}, \mathrm{lgd}_t, r_t, b_t) - l_{t-1}) + \delta \quad (1)$$

where

l_t := leverage at time t

κ := adjustment speed of capital structure (towards l^*)

$l_t^*(\cdot)$:= optimal capital structure at t

3.2. Modelling the Capital Structure Target

Although most previous empirical studies on capital structure determinants apply a linear regression model, the optimal capital structure is probably not a linear function of company characteristics. Assuming that ex ante, the direction of the agency cost and benefit effects and of the information effects of leverage on optimal capital structure is not unambiguous, I suggest that two company-specific characteristics dominate the capital structure choice: Business risk and expected losses in default. This is equivalent to the idea of the "trade-off" theory on corporate capital structure choice. While the undiscounted debt-tax shield effect is, roughly, a linear function of leverage and the interest rate,[1] the expected costs of financial distress are a nonlinear function of leverage: leverage increases the probability of financial distress, but in a simplified world, does not impact on the loss of firm value in case of distress. Hence, the optimal capital structure l_t^* is modelled as in (2): l_t^* maximizes the expected net present value of the tax shield of debt minus the expected net present value of the costs of financial distress. Relevant company-specific variables are business risk, measured as the volatility of changes in total assets, and loss given default, measured as the proportion of assets lost in case of default:

$$l_t^*(r_t, \sigma_{S,t}, \mathrm{lgd}_t, b_t) = \arg\max_l \sum_{\tau=t+1}^{\infty} e^{-r_t \cdot (\tau - t)} E_Q\left[l \cdot S_\tau \cdot (r_t + c) \cdot \varpi \cdot (1 - C_\tau(S_\tau, l))\right] -$$

[1] Titman and Wessels (1988) found that their company-specific non-debt-tax shield characteristic, suggested as a substitute for the debt-tax shield effect, is not significant in explaining capital structure. Hence, it suggests that the linearity of the debt-tax-shield effect is not disturbed by non-debt-tax shields.

$$\sum_{\tau=t+1}^{\infty} e^{-r_t \cdot (\tau - t)} E_Q[\text{lgd}_t \cdot S_\tau \cdot M_\tau(S_\tau, l)], \qquad (2)$$

where

r_t := riskfree interest rate in year t

ϖ := tax rate on corporate income

c := spread above the riskfree rate to be paid on debt

S_τ := firm value at τ

$$C_\tau := \begin{cases} 1 & \text{if the firm has defaulted between t and } \tau \\ 0 & \text{else} \end{cases}$$

$$M_\tau := \begin{cases} 1 & \text{if the firm has defaulted between } \tau - 1 \text{ and } \tau \\ 0 & \text{else} \end{cases}$$

lgd_t := fraction of asset value which is lost in default

$\sigma_{S,t}$:= asset volatility

b_t := fraction of asset volatility entailed by systematic risk.

and where E_Q is the expectation with respect to the risk-neutral probability measure Q. The latter two variables $\sigma_{S,t}$ and b_t determine the distribution of S_τ, the value of the firm's assets, which is modelled as a stochastic process under Q as described in section 2.3. The future life of the firm is divided into subperiods, where τ stands for the end of a subperiod. Tax shield is the product of the interest rate paid on debt (r_t+c), the tax rate ϖ and the amount of debt (leverage l · value of total assets S_τ). The corporate tax rate is set equal to the average U.S. combined corporate taxrate (39%). [2]The tax shield is realized each period provided the firm has not defaulted before. Because the tax shield in the period followed by τ is zero if the firm has defaulted, the expectation of the tax shield needs to be taken over those states where the firm has survived until τ and those states where the firm has defaulted until τ, which is

[2] Graham (2000) studies the debt tax shield effect in detail.

captured by the "cumulative" default indicator C_τ. As a guess on c, the average spread between the riskfree rate and the current yield on bonds with a leverage ratio comparable to l is used.

The costs of financial distress are the amount of firm value lost due to default, and these are indirectly borne by the company in the form of worse conditions in any contract with a stakeholder into which the firm enters. The costs of financial distress associated to τ are equal to the wealth loss borne by any creditors who hold claims against the assets of the firm, which is represented by the product of loss given default (lgd) and the value of the firm's assets at τ, S_τ. The expected loss in case of default is only realized once, at the time of default. Thus, the expectation is taken over those states where the firm has survived until τ and those states where the firm has survived until $\tau - 1$, but defaulted between $\tau - 1$ and τ. This is captured by the "marginal" default indicator M_τ.

3.3. Estimating the Probability of Default

This expression for l_t^* requires a specification of the probabilities of default for each subperiod of the future life of the firm, beginning in t, as a function of leverage. In order to find the marginal and cumulative default probabilities, the value of the firm's assets S_t and the level of corporate debt D_t are modelled as stochastic processes, and it is assumed that default happens as soon as S_t is equal or lower than D_t. This type of model is known as a structural model of credit risk, see Uhrig-Homburg (2002) for a survey of various alternative specifications. A promising type of model employs a jump-diffusion process for the company's assets, recognizing that the firm's value is subject to (mostly firm-specific) jumps related to rare, but high-impact effects such as new products or the loss of a major customer, and subject to (mostly economy-wide) diffusion effects such as a decline of overall demand.

Zhou (2001) suggests such a model, where the value of debt (i.e. the default barrier) is kept constant over time. The model used in this study follows his basic idea but applies some advancements. The value of assets is assumed to follow the following process:

$$dS = (r - \lambda_q v_q)Sd\tau + \sigma_D S\sqrt{d\tau}dW + (J_q - 1)dY\ . \qquad (3)$$

$r :=$ riskfree rate
$v_q := E[J_q - 1] = E[\mu_{\pi q} + 0{,}5\sigma_\pi^2] - 1$
$\sigma_D :=$ volatility of assets implied caused by the diffusion process
$d\tau :=$ marginal unit of time
$J :=$ jump size, $\ln(J) \sim N(\mu_{\pi q}, \sigma_\pi^2)$
$\sigma_\pi :=$ volatility of assets caused by the jump process
$dW :=$ Brownian motion, $dW \sim N(0,1)$
$dY :=$ Poisson - process with parameter λ_q

It is assumed that jumps represent firm-specific, i.e. unsystematic variations in asset value, i.e. the proportion of asset volatility caused by the diffusion process is equal to the ratio of the volatility of an appropriate stock index - as a measure of the amount of systematic risk - to the volatility of the firm's share. Equity volatility is partially determined by companies' leverage, so an adjustment is applied to the estimate of the proportion of systematic risk by multiplying by the ratio of average leverage of index components to company leverage:

$$\sigma_D = b \cdot \sigma_S \qquad (4)$$

where

$$b = \frac{\sigma_{X,index}}{\sigma_{X,ges}} \cdot \frac{\bar{l}_{index}}{l}$$

$\sigma_{X,index} :=$ volatility of stock index
$\sigma_{X,ges} :=$ volatility of the company's share price
$\sigma_S :=$ volatility of the firm's assets
$\bar{l}_{index} :=$ average leverage of index component firms
$l :=$ leverage of firm

Knowing the total asset volatility and the amount of systematic risk allows to derive the jump process volatility σ_π^2 (see Zhou (2001), p. 2023):

$$\sigma_S^2 = \sigma_D^2 + \lambda_q \sigma_\pi^2. \quad (5)$$

Payouts in the form of dividends are modelled implicitly. As dividend payouts change the capital structure, it is assumed that these payments are either set off by the subsequent adjustment, if they lead to a higher deviation from the target structure, or that they form part of the adjustment, if they decrease the deviation from the target. While Zhou (2001) assumes a constant level of debt, I argue that firms adjust their capital structure towards a target leverage. Therefore, the amount of debt needs to be modelled explicitly. The value of debt D_τ is modelled as follows, where κ is equivalent to the adjustment parameter in (1):

$$D_0 = l^* \cdot S_0 \quad (6)$$

$$D_{\tau+1} = D_\tau + \kappa\left(\frac{D_\tau}{S_{\tau+1}} - l^*\right) \cdot S_{\tau+1}. \quad (7)$$

For each l^*, the solution to this model provides an estimate of the marginal and cumulative default probabilities as a function of the parameters riskfree rate, asset volatility, systematic portion of asset volatility and loss given default. The solution to the model is found by employing a Monte-Carlo-simulation (for details refer to Zhou(2001)).

3.4. Calibrating the Structural Model of Credit Risk

To apply the structural model, the debt level adjustment parameter κ and the jump process parameters $\mu_{\pi q}$ and λ_q need to be specified exogenously. The probabilities of default from the jump-diffusion model can be used to calculate the value of a risky bond, and thus, the implied credit spread. The bond value is calculated under the risk-neutral measure, i.e. the expected return on the firms' assets is set equal to zero, and the payoffs are discounted with the riskfree rate – a standard result from the derivative pricing literature. This, at the same time, implies that the jump process parameters $\mu_{\pi q}$ and λ_q must as well be specified under the risk-neutral measure. Calibration of the model with respect to the parameters κ, $\mu_{\pi q}$ and λ_q

is achieved by searching for those values where the distance between spreads implied by the model and empirically observed average credit spreads is minimized. The solution is κ = 0.125, $\mu_{\pi q}$ = -0.5 and λ_q = 0.15. Figure 1 illustrates the fit between model-implied spreads and empirical spreads. For each rating category, based on a total of 100 representative companies, average parameter values for asset volatility, the systematic portion of total risk and leverage were isolated. Representative firms where chosen by randomly selecting from all firms with assets of more than 1 billion USD for which an issuer rating could be obtained. Altman and Kishore (1996) have undertaken an extensive study on recovery rates of corporate bonds. Recognizing that empirically, rating seems not be a major determinant of loss given default (see Altman and Kishore (1996), table 6), we use their average recovery rate of about 40% to derive an lgd estimate of 0.6. For each maturity between 1 and 10 years and each rating category, representative parameter values are used to calculate model-implied credit spreads. Empirically observed credit spreads by rating and maturity are taken from Almeida and Philippon (2007) who study corporate bond spreads during the period 1985-2004. As credit spread, the difference between the observed credit spread for each rating and each maturity and the credit spread for one-year AAA bonds is used (following Almeida and Philippon's idea who correspondingly calculate market-implied risk-adjusted costs of financial distress). If unsystematic default risk could easily be diversified and if jumps are (mostly) firm-specific, then creditors would not require a risk premium for jumps, and if jump risk is not priced, those parameter values will be identical to the values under the real probability measure. However, my model also allows for priced jumps, which is a reasonable assumption given transaction costs and other restrictions in diversifying credit risk.

3.5. Solving the Structural Model by Simulation

Solving the structural model of credit risk for finding estimates of C_τ and M_τ requires a computationally intensive Monte-Carlo-type simulation. The simulation is constructed

following Zhou (2001). The time horizon (10 years) is discretized (into n = 120 periods which correspond to months), the asset value process is simulated by sampling from the diffusion process and from the jump process both specified in a risk-neutral world (see Zhou (2001), p. 2021 for details), and risk-neutral default probabilities are calculated by counting defaults (i.e. when the asset value process is "stopped") against the total number of samples. To account for the discretization bias, the asset value process is stopped between two time-points with a frequency equivalent to the probability of default for the interim period, calculated using the concept of a Brownian bridge as described in Baldi, Caramellino and Iovino (1999). For combinations of possible parameter values, the optimal capital structure is found by searching that l^* where the expected net present value of the tax shield of debt minus the expected net present value of the costs of financial distress is maximized. Maximization is achieved by applying a the simple idea of a simplex initially suggested by Nelder and Mead (1965).

3.6. Interpolating the Optimal Capital Structure Function

As the computation of marginal and cumulative default probabilities is costly regarding computation time, I discretize the range of reasonable values of the arguments of the optimal capital structure function into a number of 4 (riskfree rate) × 24 (asset volatility) × 9 (systematic portion of risk) × 11 (loss given default) = 9,504 datapoints and evaluate the function for each of those datapoints. Then, an algorithm for multidimensional spline interpolation on equidistant grids is used to calculate the function $l_t^*(r_t, \sigma_{S,t}, \text{lgd}_t, b_t)$. Because of the multidimensionality of the problem, the interpolation itself is costly, too, thus I ex ante determine the optimal capital structure for 6,044,876 datapoints. l_t^* is then determined by finding the optimal capital structure for that datapoint which is closest to the company's parameter vector. For interpolation, I follow the idea of Habermann and Kindermann (2007)

who suggest a simplified interpolation algorithm for multidimensional problems that exploits the presence of an equidistant grid of observed datapoints.

3.7. Measurement Model

Unfortunately, the determinants of optimal capital structure used in this model, business risk and losses given default, cannot be observed directly, however, indicators of these determinants can. I model asset volatility (business risk) and the loss given default as latent variables, indicated by four respectively three observable variables:

$$\mathbf{Y} = \boldsymbol{\mu}_y + \boldsymbol{\Lambda}\mathbf{x} + \boldsymbol{\varepsilon} \tag{8}$$

where

$$\mathbf{Y} = \begin{pmatrix} \text{AVOL} \\ \text{SVOL} \\ \text{CVOL} \\ \text{RD} \\ \text{INT} \\ \text{MTB} \\ \text{RD} \end{pmatrix}, \quad \boldsymbol{\Lambda} = \begin{pmatrix} 1 & 0 \\ \lambda_2 & 0 \\ \lambda_3 & 0 \\ \lambda_4 & 0 \\ 0 & 1 \\ 0 & \lambda_6 \\ 0 & \lambda_7 \end{pmatrix}, \boldsymbol{\mu}_y = \begin{pmatrix} 0 \\ \mu_2 \\ \mu_3 \\ \mu_4 \\ 0 \\ \mu_6 \\ \mu_7 \end{pmatrix}.$$

x is a (2×1) vector of two latent variables distributed according to

$$N(\boldsymbol{\mu}_x, \boldsymbol{\Phi}) \tag{9}$$

where

$$\boldsymbol{\mu}_x = \begin{pmatrix} \mu_{pd} \\ \mu_{\lg d} \end{pmatrix}, \qquad \boldsymbol{\Phi}_y = \begin{pmatrix} \phi_1 & \phi_{12} \\ \phi_{12} & \phi_2 \end{pmatrix}$$

and **Y** is a vector of observable variables suggested as indicators of the latent variables, four of which associated to business risk, and three of which associated to loss given default. AVOL is asset return volatility. It is taken from the solution ($\hat{S}$, AVOL) to the following

system, i.e. the Black/Scholes pricing relation for the equity, which is modelled as an option on firm value with the level of debt as the strike price[3]:

$$MC = S \cdot N(d_1) - K \cdot e^{-rt} \cdot N(d_2)$$
$$AVOL = \sigma_{MC} \cdot \frac{MC}{S \cdot N(d_1)} \qquad (10)$$

where

MC := market capitalization

S := value of assets

K := level of debt

σ_{MC} : equity volatility

SVOL is the volatility of sales divided by the average volume of sales. CVOL is the volatility of the ratio of costs to sales, and RD is the ratio of research and development costs over assets. Observed volatilities are calculated from the last three years before the observation date. These variables are suggested to be closely related to asset volatility. While AVOL is a direct estimate of this figure, the combination of SVOL and CVOL disaggregates the risk of changes in the company's profit: Variation in sales and variation in the ratio of profit to sales. Firms with higher research and development expenditure are suggested to be more risky because the success of these activities is predictable only to a small extent. INT is the inverse of the ratio of tangible assets over total assets and MTB is the market to book – ratio. These variables are suggested to be closely associated to the loss given default, because intangible assets often become useless once the firm cannot continue to operate, and furthermore, the market – to book ratio measures future profits ("growth options") that do not fulfil the definition of assets and most probably will be lost in case of insolvency. Research and development spending is as well interpreted as an option on future returns which will be lost in case of cessation of the company's operation. This procedure is similar to the structural

[3] d_1 and d_2 are the well known arguments of the cumulative normal distribution function $N(\cdot)$ in the Black Scholes plain vanilla call price function.

equation model employed by Titman and Wessels (1988) to identify significant determinants of corporate capital structure. AVOL and INT determine the level of the latent variables x_1 and x_2 in order to achieve identification, i.e. the appropriate elements in $\mathbf{\Lambda}$ respectively in $\boldsymbol{\mu}_y$ are set equal to 1 respectively 0.

3.8. Estimation

Because the adjustment-type model is of non-linear form, a "conditional expectation – maximization" (ECM) technique is used for estimation of the complete model. It is based on maximization of the conditional loglikelihood for the observed data $\mathbf{Y} = (\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_n)$ and the latent population variables $\mathbf{X} = (\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n)$:

$$L(\mathbf{Y}, \mathbf{X} \mid \boldsymbol{\theta}) = -0.5\Bigg[q * n * \ln(2\pi) + n \ln\left|\mathbf{\Psi}\right| + n \ln\left|\sigma_{\delta}\right| + n \ln\left|\mathbf{\Phi}\right| + \sum_{i=1}^{n} (\mathbf{x}_i - \boldsymbol{\mu}_x)^T \mathbf{\Phi}^{-1} (\mathbf{x}_i - \boldsymbol{\mu}_x) + \sum_{i=1}^{n} (\mathbf{y}_i - \boldsymbol{\mu}_y - \mathbf{\Lambda}\mathbf{x}_i)^T \mathbf{\Psi}^{-1} (\mathbf{y}_i - \boldsymbol{\mu}_y - \mathbf{\Lambda}\mathbf{x}_i) + \sum_{i=1}^{n} [\kappa(l^*(\sigma_{S,t,i}, \mathrm{lgd}_{t,i}, r_t, b_{t,i}) - l_{t-1,i})]^2 \sigma_{\delta}^{-1} \Bigg] \tag{11}$$

where
$q :=$ number of stochastic variables
$n :=$ number of observations
$\mathbf{\Psi} :=$ variance - covariance matrix of $\boldsymbol{\varepsilon}$
$\mathbf{\Phi} :=$ variance - covariance matrix of $\mathbf{x}$
$\sigma_{\delta} :=$ Var(δ)
$l_{i,t} :=$ leverage of firm - year i
$l_{i,t-1} :=$ leverage of firm - year i in the previous year

This approach has previously been employed in psychological statistics for iteratively finding the solution to nonlinear structural equation models similar to the type presented here. The idea is simple: At the r-th iteration, using the Metropolis-Hastings algorithm (see Liu and Liu (2001)) and a guess $\hat{\theta}^{(r)}$ on the parameter vector $\theta = (\mathbf{\Psi}, \sigma_{\delta}, \mathbf{\Phi}, \boldsymbol{\mu}_x, \boldsymbol{\mu}_y, \mathbf{\Lambda}, \kappa)$, a sample of the

latent variables is generated and subsequently used to find an improved estimate $\hat{\theta}^{(r+1)}$ for θ. The latent variables are sampled from

$$\exp\left\{-0.5(\mathbf{x}_i-\boldsymbol{\mu}_x)^T\boldsymbol{\Phi}^{-1}(\mathbf{x}_i-\boldsymbol{\mu}_x)-0.5(\mathbf{y}_i-\boldsymbol{\mu}_y-\boldsymbol{\Lambda}\mathbf{x}_i)^T\boldsymbol{\Psi}^{-1}(\mathbf{y}_i-\boldsymbol{\mu}_y-\boldsymbol{\Lambda}\mathbf{x}_i)\right.$$

$$\left.-0.5[\kappa(l_i^*(\sigma_{S,t,i},\mathrm{lgd}_{t,i},r_t,b_{t,i})-l_{i,t-1})]^2\sigma_\delta^{-1}\right\}. \qquad (12)$$

The improved estimate is found by conditional maximization of the likelihood separately for each element of θ: keeping all other parameters but one constant, the likelihood function is analytically maximized with respect to the one parameter not being held constant. At the next iteration, the improved estimate $\theta^{(r+1)}$ is used for generating a new sample of the latent variables. That means, at each iteration (r), the following system of equations is solved (see Lee and Zhu (2002):

$$E\left\{\frac{\partial}{\partial\boldsymbol{\theta}}L(\mathbf{Y},\mathbf{X}\mid\boldsymbol{\theta})\middle|\mathbf{Y},\boldsymbol{\theta}^{(r)}\right\}=0 \qquad (13)$$

The standard errors of parameter estimates are calculated based on the standard method of inverting the information matrix of the log-likelihood function. However, as some variables cannot be observed, the following identity is used (see Louis (1982))

$$-\frac{\partial^2 L(\mathbf{Y}\mid\theta)}{\partial\boldsymbol{\theta}\partial\boldsymbol{\theta}^T}=E\left\{-\frac{\partial^2 L(\mathbf{Y},\mathbf{X}\mid\theta)}{\partial\boldsymbol{\theta}\partial\boldsymbol{\theta}^T}\right\}-Var\left\{-\frac{\partial L(\mathbf{Y},\mathbf{X}\mid\theta)}{\partial\boldsymbol{\theta}}\right\}, \qquad (14)$$

and expectations are calculated with respect to the conditional distribution of the latent variables given the indicator variables and the parameter vector from the last iteration, which corresponds to the procedure presented in Lee and Zhu (2002).

4. Data

Each observation i represents a firm-year. Observations are taken from those firms for which a dataset exists on both Compustat North America and on CRSP. Data on market capitalization are taken from CRSP, financial statement data are from Compustat. For each

year between 1990 and 2006 where all relevant data are available for a firm, including its leverage in the previous year and stock data and sales data are available for the last three years, one firm-year is included in the dataset. 1990 is chosen as the starting point as that implies that no data is used from 1987, the year of a significant stock market crash, or before. Firms with a GICS Code of 4010, 4020 or 4030 (financial institutions) and foreign companies with ADR listed in the U.S. are excluded. This results in a final sample size of 13.778 firm-years. The riskfree rate and data on S&P 500 stock index returns are taken from Thomson Datastream. Firms have been assigned to industry groups according to the first two digits of their GICS code, and have been assigned to size groups by taking the natural logarithm of their total asset value (measured as total assets) to account for the skewness of the size distribution, rounded to a number without decimal spaces.

Insert Table 1 about here

5. Results

5.1. Optimal capital structure

The model of optimal capital structure results in a mapping that relates asset volatility and loss given default to a leverage target, given the riskfree rate and the overall market volatility as a measure of systematic risk. Table 2 reports results of the optimization model for different sets of input data. The optimal capital structure is monotonously decreasing in both default probability and default loss intensity, reaching 55.9% for firms with average asset volatility and low lgd, and approaching as low a value as 5.7% for firms with a lgd of 0.5 and a high asset volatility of 0.6.

Insert Table 2 about here

5.2. Convergence Behaviour

The iterative approach to estimating the parameters means that it is not possible to determine with certainty whether the estimates in the current iteration are optimal. Here, the iteration is stopped when the change of parameter estimates from one iteration to another is sufficiently small. Convergence of parameters can be visualized by observing their value at each iteration, as presented in Figure 1. The convergence behaviour indicates that 150 iterations are sufficient for reliable estimates.

Insert Figure 1 about here

5.3. Parameter Estimates

The estimation procedure results in a simultaneous solution to the complete set of 24 parameters. The linear relation between firm characteristics and latent variables is provided by the λ estimates ('factor loadings'), which are all positive. μ_σ and μ_{lgd} are the means of the distribution of the latent variables and their values are reasonable; the loss given default estimate of 0.62 corresponds to the empirical result of an overall average recovery rate of 0.4 observed by Altman and Kishore (1996). Asset volatility varied considerably over time; its 1990 mean[4] was 0.27, in 2000 in was about a third higher (0.36). lgd values varied, too, but to a lesser extent: mean lgd was 0.56 in 1990, but 0.63 in 2000. The adjustment speed amounts to 0.16, which means, on average, it would take a firm six years to reach its capital structure target albeit any unexpected developments.

Insert Table 3 about here

[4] To calculate this mean, for each firm-year, the expectation of the latent variables over a sample of 300 simulated values using the parameter values of the last iteration was calculated, and then, these means were averaged over all firms observed in 1990 respectively 2000.

The simultaneous estimation procedure renders it less straightforward to interpret the significance of coefficients compared to OLS regression coefficients. The significant λ coefficients demonstrate that the indicator variables exhibit a significant relation to the latent variable, where, at the same time, the significant adjustment speed parameter indicates that the latent variable is informative in determining the target capital structure. The adjustment speed parameter is 0.16, and this is within the range of previous empirical results from linear type models applied to large panel datasets, such as Fama and French (2002), who report measures between 7% and 17%, or e.g. Flannery and Rangan (2006), who report an adjustment speed of 30%. The dispersion of these results indicates that for measuring the adjustment speed, specification of the target is crucial. This finding is also supported by the results from D'Mello and Farhat (2008) who find that results of regression models for capital structure adjustments are sensitive to the proxy chosen for optimal capital structure. Therefore, both for this study and previous approaches, inference about the true adjustment speed is limited because neither approach can be considered a close-to-perfect specification of the target. A linear specification does not reflect economic causal relations appropriately; our nonlinear approach is restricted to the effects predicted by the trade-off theory. However, it can be argued that specifying and solving the optimization problem inherent in capital structure decisions is a first step towards a better approximation of the true target. Our results are different to those from Titman and Wessels (1995) who applied a linear structural equation framework to the determinants of the *level* of leverage. There, neither volatility nor future growth were significant determinants of the debt ratio. Future growth and volatility, on the other hand, are main drivers of our latent variables asset volatility and loss given default.

5.4. Robustness: Parameter Estimates for Industry / Size Subgroups

Estimates for subgroups have been obtained by reestimating the complete model for subsamples. Adjustment speed varies considerably across industry subsamples. Financial

companies (excluding banks and insurances) exhibit the lowest adjustment speed. The highest adjustment speed is observed for the health care and IT businesses, which at the same time exhibit the highest asset volatility estimates: high leverage implies that it is necessary to adjust considerably fast in order to ensure a reasonable level of leverage. The adjustment speed for all other industries lies between 0.13 and 0.19; which roughly corresponds to reaching the target in between 5 and 7 years.

Insert Table 4 about here

Industry-specific estimates provide the unsurprising result that asset volatility is highest among healthcare firms which heavily rely on risky research and development activity, and IT firms, whose business is technology driven and highly competitive. For other industries, it can be seen that asset volatility is moderate, i.e. between 0.14 and 0.2, except for utility companies, where it is lower than 0.1. This is in line with the intuition that both production and sales risk in this industry is rather low. High lgd values around 0.75 are prevalent in R&D intensive healthcare and IT businesses, where insolvency triggers noticeable impairment of intangible assets and growth options. Furthermore, it is surprising to see an lgd value for firms in the financial services industry, except for banks and insurances, of as high as 0.88. In other industries, lgd values are moderate and lie between 0.4 and 0.56.

Insert Table 5 about here

Looking at the adjustment speed and asset volatility estimates by size, it becomes apparent that both measures decrease remarkably robust with firm size. This finding is consistent with the idea that larger firms are more diversified and thus, less risky. While asset volatility amounts to nearly 0.58 for the smallest firms in the sample, it is around 0.15 for the largest

firms. The interpretation of the lower adjustment speed for large firms is less straightforward. Three alternative explanations are plausible. First, smaller firms incur lower adjustment costs. This could be the case when smaller firms rely on short-term bank debt, whereas large firms tend to issue long-term bonds which are more difficult to redeem. Furthermore, large firms are likely to pay dividends, even if profits are low, in order to uphold the image of providing a steady dividend stream to equityholders. At the same time, it might be easier for small firms to withhold dividends when equity needs to be preserved in the company. Second, firms with higher risk are required to adjust faster towards reasonable levels of capital structure just because for those firms, deviations from the target are more expensive. If a deviation from the target for a low-risk firm for a year would mean a moderately higher cost of capital, for a high-risk firm it might imply a remarkable threat to its survival. Third, the trade-off model presented here might work reasonably well for small firms, but not so for large firms. This would be consistent with the idea that other determinants apart from the tax shield and costs of financial distress are more important to large firms, such as agency costs and signalling as well as market-timing effects. If ownership is separated from management, and if ownership is dispersed as in large firms, under- and overinvestment problems become worse, and signalling and market timing is important mainly for firms that regularly issue capital on the market, which also mainly applies to large firms. When looking at the average lgd estimates for different size groups, no significant pattern can be observed. Variation in lgd across size groups is moderate compared to variation across industries.

6. Goodness of Fit

It has to be acknowledged that it is difficult to use goodness-of-fit measures to assess the quality of statistical models. On the other hand, suggesting a nonlinear model to explain capital structure adjustments requires at least a rough assessment of how well the model fits the observed data, i.e. whether the nonlinearly estimated capital structure target allows for a

reasonable guess on firms' adjustments. Moreover, it would be desirable to have a goodness-of-fit measure that, at least in a rough manner, can be compared to the fit of a linear-type model which employs the same range of variables as determinants of target leverage. However, a standard goodness of fit – measure for nonlinear SEM has not yet been found. This problem has previously been identified by Mazanec (2007). Therefore, I use two attempts to measure goodness of fit, which provide close to identical results. The goodness of fit measure for the nonlinear SEM is calculated as 1 minus the ratio of the sum of the squared differences between the observed capital structure adjustment and the modelled capital structure adjustment:

$$\text{nonlinear SEM fit} = 1 - \frac{\sum_{i=1}^{n}\left[(l_{i,t} - l_{i,t-1}) - (l^{*}_{i,t} - l_{i,t-1})\right]^2}{\sum_{i=1}^{n}\left[(l_{i,t} - l_{i,t-1}) - \sum_{i=1}^{n}(l_{i,t} - l_{i,t-1})\right]^2} \qquad (14)$$

The modelled capital structure adjustment is the product of the estimated adjustment speed and the adjustment towards the optimal capital structure, where the latter is calculated using the expectation of the two latent variables. This expectation is calculated, separately for each firm-year, by drawing 300 samples from the distribution (12) using the parameter vector obtained in the last iteration. Another goodness-of-fit statistic is obtained by using the modelled capital structure target, calculated by using the expectations of the latent variables as arguments for the l* function in least squares-regression (I) and calculating the R^2 measure. In order to compare the fit of the nonlinear structural model to using a linear combination of company characteristics as target leverage, nonlinear[5] least-squares regression (II) is calculated.

Regression (I): $dl_t = k\,(l_t^*(\,E[\sigma_{S,t}], E[\text{lgd}_t], r_t, b_t) - l_{t-1})$

[5] The regression itself is nonlinear, because products of coefficients are estimated. However, the target leverage is specified as a linear combination of company characteristics, that is, $\alpha+\beta\mathbf{w}$. In the literature, regression II is usually transformed into a regression where l_t is the dependent variable and l_{t-1} ocurs only on the RHS. This, however, implies that it is not possible to measure goodness of fit with regard to adjustments to leverage. I estimated the transformed model, which results in an R^2 of 80.2: the determinants *and* l_{t-1} explain 80.2% of the variation in l_t.

Regression (II): $dl_t = k ((\alpha + \beta \mathbf{w}) - l_{t-1})$

where

$dl_t = l_t - l_{t-1}$

l_t = leverage at time t

k = adjustment speed

l_t^* = optimal leverage

α, β = regression coefficients

w = vector of company characteristics, **w** := (AVOL, SVOL, CVOL, RDRATE, INTAN, MTB)

Insert Table 6 about here

When comparing goodness-of-fit, it needs to be kept in mind that regression (I) captures variation in capital structure adjustments based on the trade-off between debt tax shield and costs of insolvency, whereas regression (II) captures any relationship between firm characteristics and target leverage, including relationships implied by e.g. agency cost effects, signalling effects and market timing effects. Comparison of the fit of the nonlinear model and the linear model shows that the trade-off model is capable of explaining nearly as much variation in capital structure adjustments as the atheoretic linear model. That means, either, the trade-off idea dominates capital structure decisions, or, the linear model does not capture the relationship between determinants and target leverage in an appropriate way. This supports the idea that the trade-off between the tax shield effect and insolvency risk does have a significant impact on dynamic capital structure decisions.

Insert Table 7 about here

There is considerable difference between the fit of the nonlinear SEM and the fit of regression (II) for two industries, namely the IT business and utilities. Causal theories different from the trade-off theory seem to dominate capital structure decisions for these industries, and these theories apparently are consistent with a linear relationship between firm characteristics included in **w** and target leverage, which can be seen from the high R^2 measures; whatever these theories will be.

Insert Table 8 about here

While the fit of the trade-off model is just as good as the fit of the linear model for small firms, this pattern changes when considering large firms. While the linear model for the target provides a moderate fit, the trade-off model is not capable of explaining any of the adjustments to leverage of large firms. This implies that there must be more than transaction costs that could prevent large firms from actively managing their capital structure. Rather, large firms seem to adjust their leverage, too, but seem to follow rules different from the trade-off theory when setting their target leverage. However, it can still be observed that the adjustment speed and the fit decreases with firm size, when modelling the target in a linear way. This also supports the idea that large firms in general adjust slower, be it for higher transaction costs or for reasons associated to their lower risk profile.

7. Conclusion

Modelling the capital structure target as a linear combination of company characteristics has the result that any theory which implies a relation between such a company characteristic and the capital structure target can receive support by observing a significant coefficient. This, however, means that linear regression models will not allow rejecting a theory except if *any* other theory would imply an insignificant relation or a relation with a different sign. This

paper sets up the optimization problem for capital structure choice based on the trade-off between the debt tax shield and expected costs of insolvency, and solves for optimal leverage as a function of two company characteristics: asset volatility and losses in case of corporate default. Due to the unobservability of these, a nonlinear structural equation model is developed to simultaneously measure these latent variables and estimate an adjustment-type model for corporate capital structure, which allows testing the trade-off theory in isolation. The nonlinear approach provides strong evidence that capital structure decisions are based on the trade-off theory in small and medium-sized firms, whereas for large firms, other causal effects seem to dominate. By comparing the goodness of fit of an a-theoretical specification of target leverage as a linear combination of company characteristics to the nonlinear model for small and medium-sized firms, we see that the nonlinear trade-off model explains virtually as much of the variation in adjustments to leverage as the linear model. The latter approach additionally captures various other effects beyond the trade-off such as agency cost effects, signalling and market timing effects. However, we still cannot learn how much of the variation in capital structure is truly determined by the trade-off concept. If, for example, agency cost effects would be incorporated into the nonlinear model explicitly by estimating the marginal effect of debt on agency costs, an even better proxy could be found compared to the proxy used here. Hence, future work might bring about advancements with respect to an explicit specification of target leverage, rather than purely statistical linear specifications. The results illustrate that applying nonlinear techniques is essential for testing capital structure *theories* in corporate finance, rather than testing the significance of determinants, because the decision-making processes of individuals respectively firms usually do not follow linear rules.

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Table 1: Summary Statistics

Mean, median and standard deviation of firm-specific variables for the complete sample over all years (13778 observations, from 1990 to 2006). An observation is defined as a firm-year, i.e. an observation of a specific firm in a specific year.

	mean	**median**	**std. dev.**
leverage	0.27	0.22	0.21
asset volatility	0.35	0.28	0.28
std. dev. of sales / total assets	0.21	0.15	0.21
std. dev. of cost to sales ratio	0.16	0.02	0.56
research & development cost / sales	0.08	0.04	0.15
intangible portion of assets	0.63	0.65	0.24
market to book ratio	3.63	2.47	15.82
total assets	3,167.98	324.70	21,100.73

Table 2: Optimal Capital Structure

Solutions to the optimal capital structure problem, by asset volatility respectively by loss given default. The figures represent the optimal debt to equity ratio. (The systematic portion of asset volatility is set equal to 0.75; r = 0.05, κ = 0.125, $\mu_{\pi q}$ = -0.5 and λ_q = = 0.15)

asset volatility	optimal capital structure when lgd = 0.5	loss given default (lgd)	optimal capital structure when asset volatility = 0.3
0,1	42,2%	0,1	55,9%
0,2	30,8%	0,25	37,1%
0,3	20,0%	0,4	24,3%
0,4	13,0%	0,55	19,9%
0,5	7,3%	0,7	18,7%
0,6	5,7%	0,85	18,1%

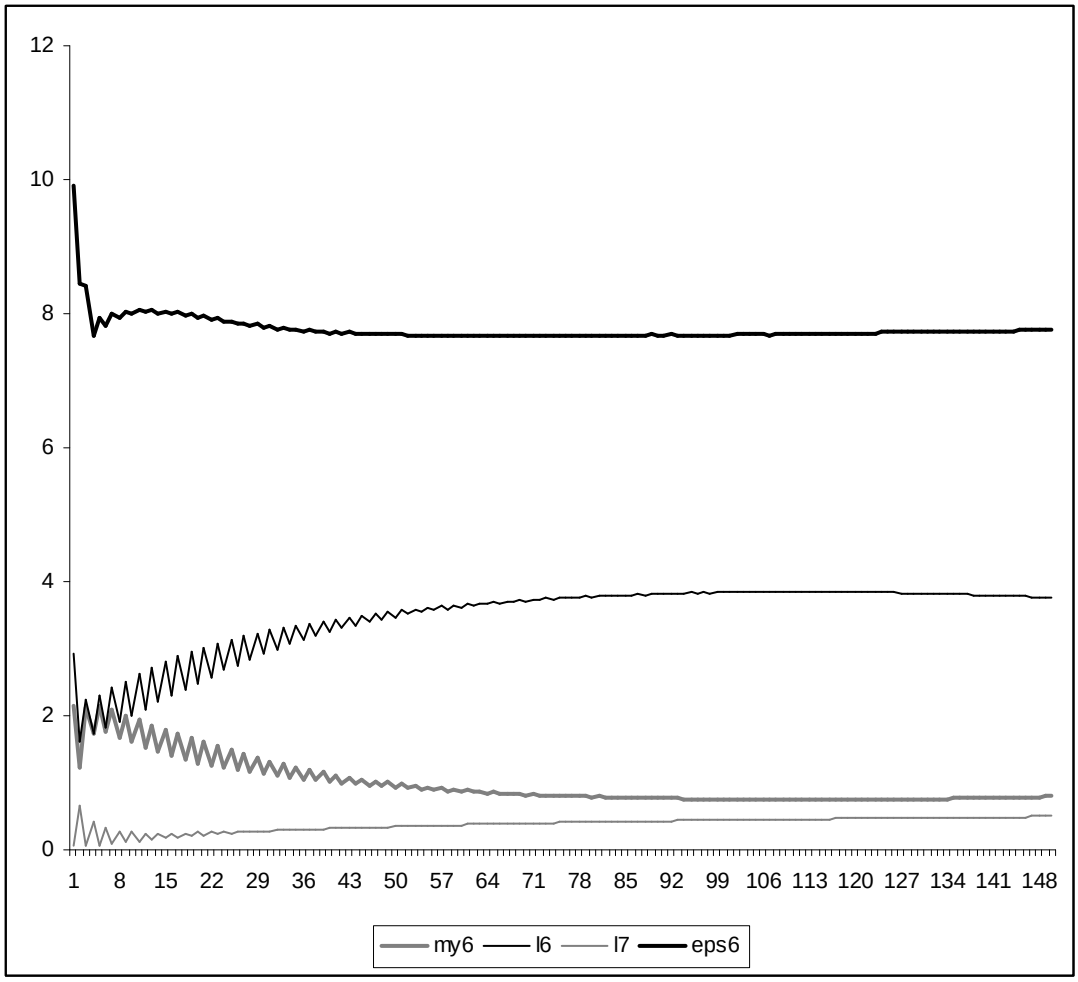

Figure 1: Some examples of *slowly* converging parameter estimates by number of iteration

Table 3: Parameter Estimates

Estimates of parameters of the nonlinear structural equation model (11) for annual adjustments to corporate leverage. The adjustment speed is κ. Estimation is accomplished by iteratively simulating the latent variables as implied by (1), (8) and (9), based on the parameter estimates of the current iteration using the Metropolis-Hastings algorithm and updating the estimates by conditional maximization of the likelihood using the simulated latent variables. The number of iterations is 150; for each firm-year (n = 13778), 100 simulated values are drawn, and std. errors are estimated by inverting the information matrix obtained by using 300 simulated values of the latent variables based on the final parameter estimates to calculate the Hessian matrix and the gradient vector.

	estimate	std. error	t-stat.		estimate	std. error	t-stat.		estimate	std. error
								ε_1	0.0561	<0.0001
μ_2	0.0519	0.0001	711	λ_2	0.4701	0.0002	1,897	ε_2	0.0321	<0.0001
μ_3	-0.8487	0.0027	-309	λ_3	3.3656	0.0083	404	ε_3	1.4098	0.0011
μ_4	-0.0683	<0.0001	-6,635	λ_4	0.4298	<0.0001	16,979	ε_4	0.0062	<0.0001
								ε_5	0.0514	<0.0001
μ_6	0.7950	0.0072	111	λ_6	3.7616	0.0177	213	ε_6	7.7593	0.0092
μ_7	-0.2292	<0.0001	-14,911	λ_7	0.4962	<0.0001	12,695	ε_7	0.0063	<0.0001
μ_σ	0.3459	0.0001	6,915					ϕ_1	0.0621	<0.0001
μ_{lgd}	0.6245	<0.0001	71,711					ϕ_2	0.0441	<0.0001
								ϕ_{12}	0.0446	<0.0001
				κ	0.1602	<0.0001	6,720	σ_κ	0.0097	<0.0001

Table 4: Parameter Estimates by Industry

Estimates and standard errors of the adjustment speed and the means of the distributions of the latent variables probability of default (μ_σ) and loss given default (μ_{lgd}) separately estimated for different industries. Firms are assigned to industry groups according to the first two digits of their GICS code.

industry	n	κ	std. error	t-stat.	μ_σ	std. error	t-stat.	μ_{lgd}	std. error	t-stat.
Energy	277	0.1534	0.0010	155	0.2695	0.0004	720	0.4825	0.0001	5,553
Materials	859	0.1707	0.0003	498	0.1434	<0.0001	3,580	0.4407	0.0003	1,425
Industrials	2066	0.1348	0.0002	591	0.2089	<0.0001	5,903	0.5684	<0.0001	22,811
Consumer Discretionary	2488	0.1960	0.0002	1,136	0.2498	<0.0001	11,486	0.4210	<0.0001	9,949
Consumer Staples	512	0.1499	0.0015	102	0.1825	0.0001	1,760	0.4588	0.0006	731
Health Care	3101	0.2411	0.0003	894	0.4669	0.0001	5,870	0.7487	<0.0001	39,596
Financials (excluding banks & insurances)	266	0.0679	0.0012	59	0.1620	0.0001	1,269	0.8837	0.0010	930
Information Technology	4127	0.2281	0.0001	1,556	0.4794	<0.0001	17,315	0.7501	<0.0001	54,276
Telecommunication Svcs	59	0.1608	0.0046	35	0.1671	0.0003	512	0.5156	0.0009	567
Utilities	23	0.1625	0.0756	2	0.0942	0.0007	126	0.4070	0.0043	96

Table 5: Parameter Estimates by Size

Estimates and standard errors of the adjustment speed and the means of the distributions of the latent variables probability of default (μ_σ) and loss given default (μ_{lgd}) separately estimated for different firm sizes. Each firm is assigned to a size category by using the natural logaritm of its total assets figure, rounded to obtain a natural number. All firms with a number $\geq$ 10 are assigned to the last group.

size group	n	κ	std. error	t-stat.	μ_σ	std. error	t-stat.	μ_{lgd}	std. error	t-stat.
1	10	0.7382	0.0004	1,989	0.5801	0.0157	37	0.5011	0.0338	15
2	1226	0.3055	0.0005	616	0.5860	0.0004	1,484	0.7041	0.0001	5,997
3	1871	0.3555	0.0014	262	0.4630	0.0002	2,675	0.6668	0.0002	3,260
4	2899	0.2290	<0.0001	30,753	0.4022	<0.0001	19,042	0.6501	<0.0001	20,435
5	2940	0.1807	0.0001	1,454	0.3243	0.0001	5,823	0.6080	<0.0001	16,040
6	2235	0.1350	0.0001	1,993	0.2709	<0.0001	29,963	0.5887	<0.0001	200,336
7	1320	0.0932	0.0001	884	0.2323	<0.0001	5,548	0.5832	0.0001	8,478
8	750	0.0768	0.0001	657	0.1773	<0.0001	16,570	0.5588	0.0001	8,939
9	350	0.0647	0.0002	296	0.1552	0.0001	1,750	0.5747	0.0008	700
10	177	0.0094	0.0002	38	0.1505	0.0002	628	0.6026	0.0253	24

Table 6: Complete Sample Goodness of Fit

The nonlinear SEM fit denotes the goodness of fit measure as presented in (14). For regressions (I) and (II), the estimated adjustment speed k, its associated t-statistic and the goodness of fit measure R^2 is presented. Both regressions use the observed adjustment to the capital structure as the dependent and a modelled adjustment as the independent variable; regression (I) is based on the nonlinearly estimated optimal capital structure, regression (II) is based on a linear combination of determinants.

nonlinear SEM fit	13.1%	
	regression (I)	regression (II)
k	0.1785	0.2242
t-stat.	45.0050	46.8682
R^2	12.8%	14.5%

Table 7: Goodness of Fit for Industry Subsamples

The nonlinear SEM fit denotes the goodness of fit measure as presented in (14). For regressions (I) and (II), the estimated adjustment speed k, its associated t-statistic and the goodness of fit measure R^2 are presented. Both regressions use the observed adjustment to the capital structure as the dependent and a modelled adjustment as the independent variable; regression (I) is based on the nonlinearly estimated optimal capital structure, regression (II) is based on a linear combination of determinants.

	nonlinear SEM	**regression (I)**			**regression (II)**		
industry	**fit**	**k**	**t-stat.**	**R^2**	**k**	**t-stat.**	**R^2**
Energy	14.0%	0.2002	7.0285	14.8%	0.1827	5.4663	16.7%
Materials	14.2%	0.1880	12.0561	14.3%	0.2878	13.8915	19.8%
Industrials	10.6%	0.1487	15.9608	10.7%	0.2102	17.0856	12.7%
Consumer Discretionary	17.2%	0.2109	22.8827	17.3%	0.2330	21.5285	17.7%
Consumer Staples	11.5%	0.1576	8.2226	11.5%	0.2007	8.7965	16.3%
Health Care	14.2%	0.2497	22.7092	14.2%	0.2986	24.8563	17.9%
Financials	4.6%	0.0743	3.6416	4.6%	0.1445	4.7802	9.9%
Information Technology	13.9%	0.2140	25.9031	14.0%	0.3241	31.6244	21.3%
Telecommunication Svcs	10.1%	0.1591	2.6005	10.1%	0.4869	6.1094	60.8%
Utilities	6.9%	0.1978	1.3375	7.1%	0.4675	1.6034	68.6%

Table 8: Goodness of Fit for Size Subsamples

The nonlinear SEM fit denotes the goodness of fit measure as presented in (14). For regressions (I) and (II), the estimated adjustment speed k, its associated t-statistic and the goodness of fit measure R^2 are presented. Both regressions use the observed adjustment to the capital structure as the dependent and a modelled adjustment as the independent variable; regression (I) is based on the nonlinearly estimated optimal capital structure, regression (II) is based on a linear combination of determinants. Results are presented for different sizes of firms: each firm is assigned to a size category by using the natural logarithm of its total assets figure, rounded to obtain a natural number. All firms with a number $\geq$ 10 are assigned to the last group.

	nonlinear SEM	**regression (I)**			**regression (II)**		
size	**fit**	**k**	**t-stat.**	**R^2**	**k**	**t-stat.**	**R^2**
1	23.9%	0.4897	2.7022	37.0%	0.0006	0.0003	85.5%
2	24.4%	0.3513	20.3773	24.8%	0.3428	18.8367	24.9%
3	26.8%	0.3361	26.9288	26.9%	0.3720	25.1833	26.4%
4	14.7%	0.2229	22.5100	14.7%	0.2648	23.4435	17.5%
5	12.1%	0.1820	20.1051	12.1%	0.2242	20.9252	13.8%
6	8.0%	0.1353	14.1102	8.0%	0.1923	16.5943	13.6%
7	4.4%	0.0918	8.0454	4.4%	0.1527	10.9043	10.8%
8	3.9%	0.0766	5.5721	3.9%	0.1580	8.3430	11.9%
9	4.1%	0.0688	3.8883	4.2%	0.1346	5.0504	9.9%
10	0.1%	0.0099	0.6947	0.1%	0.0593	2.4185	19.4%

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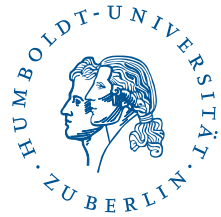

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