Denis Marinšek

Multilevel Regression and Cluster Confounding in Finance

Study of Corporate Capital Structure

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INTRODUCTION

Financial studies, performed on panel data, typically exhibit time-series and cross-sectional dependency of observations. By using European firms, I demonstrate that multilevel regression is a technique that effectively controls for both sources of dependency. It also offers some important advantages over other regression techniques (i.e. it improves prediction, it allows controlling for structure of the data, etc.). I demonstrate these effects on the issue of capital structure, an area that has been extensively studied in finance. Capital structure is chosen for various reasons. First, theoretical explanations and allied empirical testing of corporate capital structure decisions has been an ongoing focus of financial research for over 50 years (Rajan & Zingales, 1995; Hovakimian, Opler, & Titman, 2001; Lemmon, Roberts, & Zender, 2008; Frank & Goyal, 2008; Lemmon & Zender, 2010), yet, the factors that influence such decisions remain elusive (Frank & Goyal, 2009). In their recent paper, Kayo and Kimura (2011) argue that higher-level determinants are important when evaluating capital structure decisions. One of my goals is to assess whether and to what extent modeling capital structure with multilevel regression improves the model fit, compared to other regression techniques. Second, capital structure analyses are often used to estimate and predict a firm's target capital structure. The estimates are then used to assess the speed of adjustment of leverage ratios toward these predefined targets (e.g. Byoun, 2008; Marinšek, Pahor, Mramor, & Luštrik, 2016) or to determine the impact of deviations from target (e.g. too high leverage) on a firm's performance (e.g. Graham & Leary, 2011; Gonzales, 2013). As Gelman (2006) argued, one of multilevel regression key features is improved accuracy of model predictions. Third, the majority of capital structure research is executed on US samples. With a large sample of firms across 25 European countries, the robustness of capital structure determinants can be compared to past empirical findings. Fourth, to the best of my knowledge, at their peril existing empirical studies on capital structure do not address the cluster confounding (i.e. separating within- and between-group effects) of traditional trade-off variables of capital structure theory (e.g. tangibility, size, profitability).

In an attempt to better and more reliably explain the capital structure heterogeneity, I analyze firms' indebtedness over the period 2005–2011, using a sample of 8,777 firms, operating within 18 industries and 25 European countries. Many researchers empirically showed that both industry and country norms importantly determine firms' capital structure dynamics (e.g. Stonehill & Stitzel, 1969; Toy, Stonehill, Remmers, Wright, & Beekhuisen, 1974; Ferry & Jones, 1979; Bradley, Jartell, & Kim, 1984; Frank & Goyal, 2009; Ruah & Sufi, 2010). Since it can be expected that firms operating within the same industry or the same country are similar to a certain extent and thus not completely independent, a proper regression technique should be used. Performing OLS regression analysis on such data, assuming that these observations are independent, would lead to biased results (Tabachnick & Fidell, 2012; Gelman & Hill, 2007).

An advanced regression technique, called multilevel regression, is an elegant solution for the unmet assumption of independency of observations because it assumes that observations within the same group (cross-sectionally or longitudinally) are more similar than they would be by chance. Based on the structure of the data, I use multilevel regression that accounts for cross-sectional and time-series dependency at the same time, the two forms of dependency very common in many financial studies. The former one is the dependency of residuals across firms in a given year – cross-sectional dependency, while the latter one is the dependency of residuals of a firm that is observed over the years – time-series dependency. I also show that cluster confounding, as highlighted by Bartels (2008), should carefully be considers in financial and other economic studies. In addition to get an innovative overview of corporate capital structure heterogeneity, multilevel regression is also used for precise estimations of the target mix of different sources of financing. Graham and Leary (2011) recently argued that even if convergence toward the target capital structure is proved (see Lemmon et al., 2008 and Marinšek et al., 2016), there remains an open question as to which economic forces motivate within-firm movements of leverage. I try to provide some answers by using multilevel regression.

In the first chapter I explain the theory of multilevel regression and cluster confounding. I clarify the difference between OLS regression and multilevel regression and describe main advantages of using the latter one. In the second chapter I give an overview of corporate capital structure theory and explain why multilevel regression is the appropriate statistical method for explaining corporate capital structure heterogeneity. In the third chapter I apply the multilevel regression to empirically assess the corporate capital structure theory.

I compare the results obtained by OLS regression with results of multilevel regression. Additionally, I show that without properly addressing cluster confounding, results can be highly misleading. Then I use the estimations of target capital structure, obtained by multilevel model, to explain the motives of convergence toward the target capital structure. In the conclusion I summarize the findings.

1 MULTILEVEL REGRESSION AND CLUSTER CONFOUNDING

There are two forms of dependency that pervade financial studies (Petersen, 2009). On the one hand, there is the dependency in residuals for a given firm (i.e. time-series dependency), while on the other there is the dependency in residuals across firms in a given year (i.e. cross-sectional dependency), the latter of which can be a consequence of a hierarchical structure of data. Petersen (2009) reviewed various financial studies and summarized numerous alternative estimations of standard errors, applied in the regression models, which use panel-data. He concluded that researchers typically use classical OLS standard errors, White-corrected standard errors (White, 1980), and Fama-MacBeth-corrected standard errors (Fama & MacBeth, 1973). According to Petersen (2009), both White- and Fama-MacBeth-corrected standard errors exhibit a significant downward bias because only the cross-sectional dependency is effectively controlled. Serial correlation of observations for a given firm, on the other hand, is not appropriately addressed. Accordingly, a key message from his paper is to cluster standard errors by firms, which would solve the problem of serial correlation. However, Thompson (2011) argued that standard errors that simultaneously cluster both by firm and time should be preferred in financial studies.

There is an alternative approach to model both types of dependency, called multilevel regression. Multilevel regression effectively simultaneously controls both time-sectional dependency through repeated measurements (firm-year observations are clustered within a firm), and cross-sectional dependency through data hierarchy (lower-level units, e.g. firms, are clustered within a higher-level unit, e.g. an industry). Moreover, multilevel regression allows the joint modeling of various levels of data (e.g. firm-year observations are clustered within a firm, firms are operating within an industry, and industries are grouped within a country)[1], so it can be an effective alternative statistical technique for

[1] A good example from the educational literature is the analysis of test scores (dependent variable), achieved by students (level-1 unit), who are clustered within a class (level-2 unit) and school (level-3 unit). At each level of data, different groups of explanatory variables are used to explain the result achieved on a test (e.g. level-1: gender, age; level-2: class size,

modeling financial studies. Moreover, there are papers in the context of political research that analyze advantages and shortfalls of alternative methods, comparing clustered standard errors with results, obtained by multilevel regression (e.g. Primo, Jacobsmeir, & Milyo, 2007). Notably, Gelman (2006), and Gelman and Hill (2007) argue that multilevel regression is superior to clustered standard error techniques. Arguably one of the biggest attractions of multilevel regression is that it produces separate estimates for each individual group, while effectively handling unbalanced datasets and not requiring any more assumptions than do clustered standard error techniques. Gelman (2006) concludes that compared to other regression techniques, multilevel regression is always an improvement, to varying degrees: for prediction it can be essential, for data reduction it can be useful, and for causal inference it can be helpful. Similarly, recent research has demonstrated that multilevel regression is more successful at avoiding falsely rejecting the null hypothesis due to artificially inflated testing statistics (Cheah, 2009). Cheah concluded that modeling data by controlling for its multilevel structure is a better approach than simply correcting the standard errors obtained with standard regression techniques.

A further potentially important issue that arises in financial studies is "cluster confounding" (hereafter CC). Regression techniques assume that within- and between-group effects of unit-level predictors are equal both in size and direction, however, this assumption is not necessarily true (Bartels, 2008). Bartels reexamines several published empirical studies and highlights the problematic and unreliable conclusions that are possible when CC is ignored or poorly addressed.[2] Multilevel regression allows effectively dividing within- and between-group effects into two parts, and comparing their strength.

years of experience of a teacher; level-3: school size, poverty of neighborhood surrounding a school).

[2] These examples are Global human rights abuse (Poe & Tata, 1994; Poe, Tata, & Keith, 1999), Rewarding impatience hypothesis regarding oil production in OPEC countries (Blaydes, 2005, 2006; Goodrich, 2006), and Senate voting on Supreme Court nominations (Epstein, Lindstadt, Segal, & Westerland, 2006).

1.1 Multilevel regression

Multilevel regression (also known as multilevel linear modeling, hierarchical modeling or linear mixed models) is used for research design, where data is structured in more than one level. The lowest level of data is usually defined as a subject or as a repeated measurement of a subject. These subjects or repeated measurements are then nested within higher-level units (e.g. pupils – classes – schools) (Gelman & Hill, 2007). West, Welch, and Galecki (2015) defined multilevel regression as parametric linear models for clustered, longitudinal, or repeated-measurements data that quantifies the relationship between a continuous dependent variable and various explanatory variables. It may include both fixed effect parameters associated with one or more continuous or categorical covariates, and random effects with one or more random factors. According to West et al. (2015) there are three general types of data that can be analyzed with multilevel regression. The first type is clustered data, where each unit is measured once and these units are clustered within higher level units. The second type is repeated-measurements data, where the dependent variable of each unit is measured more than once. The third type is longitudinal data, where dependent variable of each unit is measured at several points in time, usually with equal intervals. Finally, there is also a combination, called clustered-longitudinal data, which combines features of both clustered and longitudinal data at the same time. In my analysis of capital structure, leverage is measured for each firm at several points in time with equal intervals, while firms are nested within industries and countries – clustered-longitudinal data.

Multilevel regression is a technique of partial-pooling, executing an analysis that lies somewhere between the complete- versus no-pooling outcomes (Gelman & Hill, 2007). Under complete-pooling, differences among groups are completely ignored because categorical predictors are excluded from the model. Alternatively, no-pooling method treats the data as coming from totally separate groups for each categorical predictor. According to Gelman and Hill (2007), both approaches have their shortcomings. Complete-pooling suppresses variation that can be crucial for reliable inference, while no-pooling technique ignores part of cross-information, that too can be problematic for statistical inference (Bartels, 2008). While the outcomes from both techniques can be useful as preliminary estimates, the researcher should prefer the compromise of partial pooling – the result of multilevel regression (Gelman & Hill, 2007).

When there is little group-level variation, multilevel regression automatically reduces to classical regression analysis with no group indicators. Similarly, when there is a small number of groups (less than five, according to authors), there is often not enough information to estimate group-level variation. Toward the other extreme, when there is a large variation in group-level coefficients, multilevel regression is transformed to classical regression analysis with group indicators. In all other cases, multilevel regression provides more realistic analysis and more reliable statistical inference compared to classical regression techniques. Many statisticians argue that whenever applicable, strong preference should be given to multilevel regression (e.g. West et al., 2015; Tabachnick & Fidell, 2012; Raudenbush & Bryk, 2002; Hox, 2010). Furthermore, Raudenbush, and Bryk (2002) argued that multilevel regression is most effective when final results are closer to complete-pooling than to no-pooling method. Under such conditions, estimates are allowed to vary by groups while still being estimated precisely. Estimates are effectively pooled when between-group standard deviation is relatively small, meaning that groups are relatively homogenous. On the other hand, when between-group standard deviation is large, multilevel regression will not be much more effective compared to simple no-pooling estimation (Gelman & Hill, 2007). However, between-group standard deviation can always be effectively reduced by including additional group-level predictors.

Multilevel regression is ideally suited to situations in which data take a hierarchical structure, namely, that units are clustered within groups based on a degree of homogeneity in particular relevant characteristics: whenever units are clustered within groups or when the same unit is observed more than once, the independence assumption is violated (Field, 2013). The most commonly used measure for this similarity is intraclass correlation (hereafter ICC). Whenever a value of ICC is higher than 0.1, units within a cluster are assumed to have a high degree of homogeneity, which should be appropriately handled. Another important advantage of multilevel regression is avoiding two fallacies, which arise when performing an analysis at a higher level while interpreting results at a lower level (ecological fallacy), or performing an analysis at a lower level while interpreting results at a higher level (atomistic fallacy). Both fallacies can be effectively avoided by multilevel regression, which allows the intercept and slopes to vary between higher-level units (Hox, 2010).

When analyzing multilevel models, it is crucial to distinguish between fixed and random factors (West et al., 2015). Fixed factors are commonly used at analysis of variance (ANOVA) and covariance (ANCOVA). A fixed factor can be defined as a categorical or classification variable, for which all levels of interest are included. The examples of such fixed factors are qualitative covariates (e.g. gender), classification variables (e.g. region, stratum, treatment method), or ordinal classification variables (e.g. age groups). Levels of a fixed factor are selected in such a way that they represent specific conditions and can be used to define contrasts of interests in the research study. On the other hand, a random factor is a classification variable with levels that can be understood as being randomly sampled from a population of levels being studied. Not all possible levels of the random factor are present in the sample data; however, the researcher's intention is to make inference about the entire population of levels (West et al., 2015). Another crucial component of any multilevel regression is the distinction between fixed and random effects (West et al., 2015). Fixed effects, called regression coefficients or fixed effect parameters, describe the relationship between the dependent variable and explanatory variables for an entire population of units of analysis. Fixed effects can be fixed factors or continuous covariates. They can be used to describe contrast between levels of a fixed factor (e.g. between males and females) in terms of mean response for the continuous dependent variable, or they may describe the effect of continuous covariates on the dependent variable. Fixed effects are unknown fixed quantities and are estimated based on the analysis of the data, collected in a given research study. On the other hand, random effects are random values, associated with the levels of a random factor. They represent the deviations from the relationships, captured by fixed effects. They can be in a form of random intercept (representing random deviations for a given subject or cluster from the overall fixed intercept), or in a form of random coefficients (representing random deviations for a given subject or cluster from the overall fixed effect). The main goal of allowing intercept to vary across groups is to handle the increased Type I error, which occurs when groups in the hierarchical data structure significantly differ in the average value of the dependent variable (Tabachnick & Fidell, 2012).

As an example, I present the basic technique of estimation of a regression intercept with multilevel regression. I assume that I perform a partial-pooling with only group-level classification and no other predictor variables. In that case, intercept for a group *j* is estimated by *Equation 1-1*.

$$\hat{\beta}_{oj} \approx \frac{\frac{n_j}{\hat{\sigma}_w^2}\,\bar{y}_j + \frac{1}{\hat{\sigma}_b^2}\,\bar{y}_{all}}{\frac{n_j}{\hat{\sigma}_w^2} + \frac{1}{\hat{\sigma}_b^2}} \tag{1-1}$$

The multilevel estimation of intercept for group j is a weighted average of no-pooled estimate of the arithmetic mean in the group j ($\bar{y}_j$) and completely-pooled estimate over all groups ($\bar{y}_{all}$). $\hat{\sigma}_w^2$ and $\hat{\sigma}_b^2$ are estimates of within and between group variances of the dependent variable, respectively. A group with a larger sample size (n_j) contains more information and the corresponding multilevel estimate is close to the group average ($\bar{y}_j$). In the limit, as $n_j \to \infty$, the multilevel estimate would simply be the group average, $\bar{y}_j$. On the other hand, groups with small sample sizes contain less information, and the weighting pulls the multilevel estimates closer to the overall group average ($\bar{y}_{all}$). In the limit, as $n_j \to 0$, the multilevel estimate would simply be the overall average, $\bar{y}_{all}$. Weighting process thus reflects the relative amount of information available from the individual group on the one hand, and the information available from all groups on the other. A more generalized equation for estimating intercept with one predictor is written in *Equation 1-2*.

$$\hat{\beta}_{oj} \approx \frac{\frac{n_j}{\hat{\sigma}_w^2}}{\frac{n_j}{\hat{\sigma}_w^2} + \frac{1}{\hat{\sigma}_b^2}}\left(\bar{y}_j - \hat{\beta}_1 \bar{x}_j\right) + \frac{\frac{1}{\hat{\sigma}_b^2}}{\frac{n_j}{\hat{\sigma}_w^2} + \frac{1}{\hat{\sigma}_b^2}}\hat{\mu}_{\beta_0} \tag{1-2}$$

The intercept can be expressed as a weighted average of no-pooled estimate of its group $\left(\bar{y}_j - \beta_1 \bar{x}_j\right)$ and completely-pooled arithmetic mean $\hat{\mu}_{\beta_0}$. From the *Equation 1-2* it can be noticed that there is more pooling towards overall arithmetic mean when there is a small group-level standard deviation ($\hat{\sigma}_{\mathrm{b}}$), and more smoothing for groups with fewer observations (n_j) (Gelman & Hill, 2007). To summarize, multilevel regression can be understood as a method that compromises between complete-pooling, where categorical predictor for a group classification is excluded, and no-pooling, where separate model for each level of the categorical predictor is estimated. When complete-pooling method is chosen, regression analysis estimates the average that completely pools the data across all groups. That method ignores all the variation between groups. On the other hand, no-pooling analysis overstates the variation between groups and tends to make the individual groups look more different than they actually are (Gelman & Hill, 2007).

Unlike the decision for including random intercept, a random slope is used when a relationship between dependent and explanatory variable is expected to differ among groups (Tabachnick & Fidell, 2012). The decision whether to include a random slope must be evaluated for each explanatory variable separately. This can be done by testing whether the slope variance is statistically different from zero. It is important, however, to note that slopes of explanatory variables on the highest level are always fixed.

Gelman and Hill (2007) summarized some advantages of multilevel regression. They concluded that it is useful for comparing treatment effects that vary among groups, that it importantly improves prediction, that it allows controlling for structure of the data (e.g. cross-sectional dependency), that it offers more efficient inference of regression parameters, that it improves the reliability of estimated standard errors and that it is suitable for unbalanced datasets. Furthermore, assumptions of independence of errors, as assumed at standard OLS regression analysis, and of homogeneity of regression slopes, as assumed at analysis of covariance, are not required (Field, 2013). Another advantage comes when someone works with the missing observations. Many researchers argue that missing observations in longitudinal studies have only a minor effect on multilevel regression. Moreover, such estimates are more reliable compared to the use of different imputation methods for missing values (Field, 2013; Tabachnick & Fidell, 2012). An additional advantage of multilevel regression is the ability to include higher-level explanatory variables, which allow testing of between-group effects (Bartels, 2008; Tabachnick & Fidell, 2012). Higher-level predictors are often helpful at explaining lower-level differences in the intercepts and slopes. Further, Gelman and Hill (2007) argued that one important advantage of multilevel regression is the ability to estimate meaningful regression coefficients for groups with quite small sample sizes. Even with just two observations per group, multilevel model can successfully be fitted. In such cases, group-level standard deviation is not estimated precisely, but it still provides some information that allows estimation of the coefficients and variance parameters on different levels.

On the other hand, the main disadvantage of multilevel regression comes in the form of more complicated models that are harder to interpret and summarize (Gelman & Hill, 2007). An additional limitation is that multilevel regression is very sensitive to correlated predictors (Tabachnick & Fidell, 2012). Therefore, other things equal, a smaller number of relatively uncorrelated predictors should be used. A strong theoretical framework often helps limiting the number of predictors and facilitates decisions about how to treat them. The problem of multicolinearity can sometimes be resolved by just simply centering the variables (Twisk, 2006; Field, 2013). Centering can be done on group-mean or grand-mean. Often, the latter choice is safer and easier to interpret (Raudenbush & Bryk, 2002; Tabachnick & Fidell, 2012). Since multilevel regression is an extension of multiple regression, the potential distorting effect of outliers should be considered. Raudenbush and Bryk (2002) suggested that within each level of the data, both univariate and multivariate outliers are removed from the analysis.

Multilevel regression typically starts with a multiple regression model, which is gradually developed into the multilevel model (Raudenbush & Bryk, 2002). First, the series of multiple regression analyses can be performed, e.g. complete-pooling and no-pooling models. Additionally, separate regression analyses can be performed within each group of data. The main goal of the group-level predictors, however, is not merely to prove statistical differences among groups, but to get the most realistic estimates. Statistical significance should therefore not determine inclusion or exclusion of a particular predictor. However, estimating many regression coefficients can complicate the fitting procedure and can increase model complexity (Gelman & Hill, 2007). Therefore, the change in log-likelihood is the preferred measure of model fit over the traditionally used *t*-tests for fixed effects or Wald-tests for random effects. The majority of researchers thus suggest that explanatory variables on different levels are added step by step, analyzing the overall fit of the model. The reference model (i.e. the more general model, which includes both the null and the alternative hypotheses) is compared to the nested model (i.e. the simpler model, which satisfies only the null hypothesis) through the likelihood ratio test (LRT). Likelihood theory states that LRT asymptotical follows chi-squared distribution, with degrees of freedom equal to the number of additional parameters in the reference model. If the reference model has a statistically significantly lower value of –2 log-likelihood function than the nested model, this means that the overall fit of the model has improved. The theory suggests that when comparing two models that differ only in fixed effects, maximum LRT should be preferred. On the other hand, when comparing two models that differ in random effects, restricted maximum LRT must be used (West et al., 2015). When performing Wald-tests, *p*-values at variance terms should be divided by two (i.e. one-tailed test), because one is only interested if the variance is greater than the expected by chance. However, at covariance term, two-tailed test must be used (Tabachnick & Fidell, 2012). When working with non-nested models, the model with the lowest values of AIC or BIC statistics has the best fit, since the changes in values of likelihood function are not directly comparable between the models (West et al., 2015).

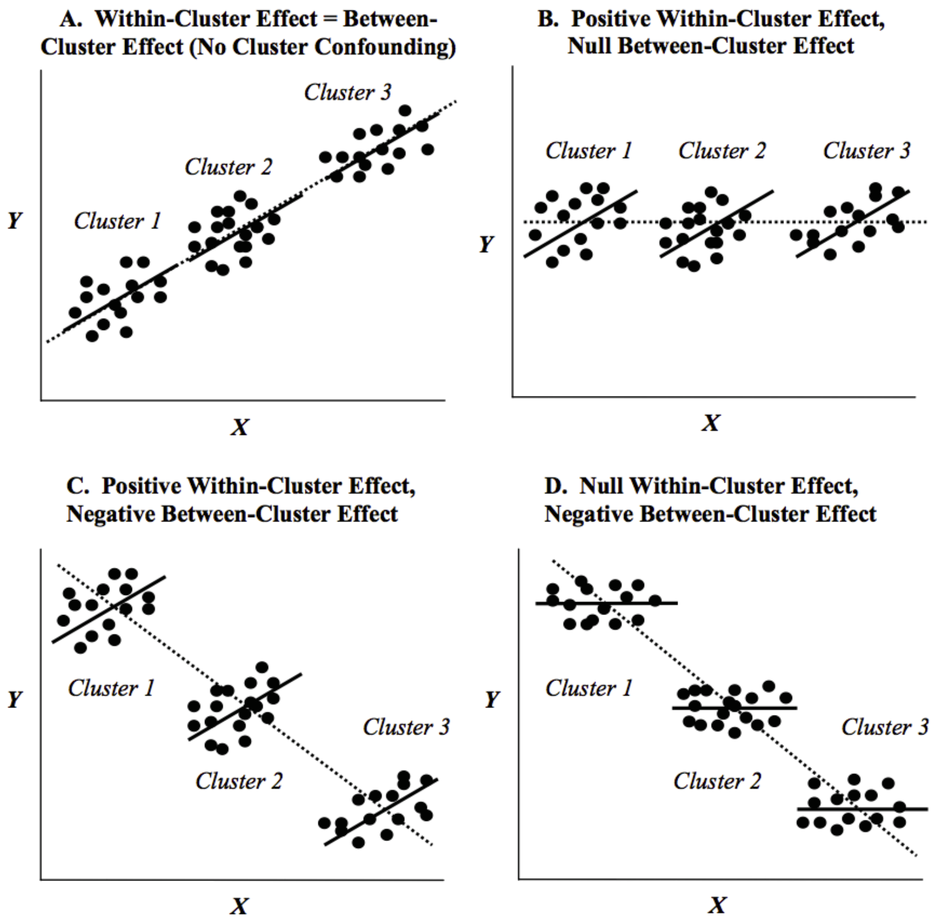
1.2 Cluster confounding

In addition to properly model the data hierarchy, cluster confounding is an important issue that needs to be carefully considered and addressed (Bartels, 2008). Multilevel regression, as any other regression technique, assumes that within- and between-group effects of unit-level predictors are equal in size and direction. *Figure 1-1* shows four possible relationships between the dependent and explanatory variable. However, only *Panel A* exhibits no cluster confounding – the relationship between variables is the same within- and between-clusters. *Panels B*, *C* and *D* show the presence of cluster confounding, which can result in misleading conclusions.

Because effects are not always equal, Bartels (2008) suggested transforming unit-level variables to within- and between-group parts. First, the group-specific arithmetic mean of X_{ijk} must be estimated, denoted as $\bar{X}_{ijk}^{b}$ (t indexes time, *i* indexes firms, *j* indexes industries, *k* indexes countries). This variable is used for estimating the between-firm effect. The within-firm effect is then estimated with the help of a new variable, denoted and transformed as $X_{tijk}^{w} = X_{tijk} - \bar{X}_{ijk}^{b}$. The components $\bar{X}_{ijk}^{b}$ and X_{tijk}^{w} are uncorrelated because within-group and between-group variations are completely separated. Additionally, specifying the model this way satisfies the problematic assumption of independence of the unit-level variable and the random effect term.[3]

[3] Hausman (1978) developed a test to assess the adequacy of this assumption.

Figure 1-1. *Cluster confounding issue*



Source: B. L. Bartels, *Beyond "Fixed versus Random Effects": A Framework for Improving Substantive and Statistical Analysis of Panel, Time-Series Cross-Sectional, and Multilevel Data*, 2008.

2 THE CASE OF CORPORATE CAPITAL STRUCTURE

In the second chapter I theoretically present the theory of corporate capital structure and explain the idea of the target capital structure. Then I graphically show the multilevel structure of the data, together with a short description of its content. Then I present the dependent and explanatory variables, used for determining the target capital structure. At the end I technically develop the multilevel model, which can be applied to the financial dataset.

2.1 Corporate capital structure

Theoretical explanation of firms' capital structures, i.e. the ratio between debt and equity in a firm's financing, has been a central issue in financial research for over 50 years. In 1958, Modigliani and Miller presented the hypothesis that under certain (unrealistic) assumptions capital structure does not affect a firm's value. Subsequent theories introduced assumptions that are more realistic and showed that capital structure affects the market value of a firm (e.g. Modigliani & Miller, 1963; Hamada, 1969; Rubenstein, 1973; Miller, 1977; Grossman & Hart, 1982). These findings led to the development of two major theories that attempt to explain the financing of firms: the *trade-off theory* and the *pecking order hypothesis*. The former is built on the idea that leverage boosts the risk adjusted return on equity (to a certain level of indebtedness), while the latter assumes that debt should only be used after internal resources are exhausted, which minimizes the overall costs of issuing new equity (Kester, Hoover, & Pirkle, 2004). However, there are theoretical disagreements and inconclusive empirical findings concerning which of the two theories better explains the observed capital structures. Fama and French (2002; 2005) argued that both theories have their strengths and weaknesses and that neither of them is able to fully explain a modern firm's capital structure. Moreover, both theories should be used as supplements in explaining the capital structure decisions of firms. As an alternative theory, Baker and Wurgler (2002) argued that the capital structure can best be understood as the cumulative effect of past attempts to time the market. However, this theory is not readily linked to the traditional determinants of capital structure (Frank & Goyal, 2009). An extensive review of capital structure theory can be found in Marinšek (2015). For the purpose of applying the multilevel modeling approach, taking the above strands of the literature on board, I select variables to fit the multilevel structure of the data.

Many empirical studies have attempted to test capital structure theories (e.g. Jensen & Meckling, 1976; Taggart, 1977; Ross, 1977; DeAngelo & Masulis, 1980; Leland, 1994; Hovakimian et al., 2001; Kester et al., 2004; Liu, 2005; Lemmon et al., 2008; Frank & Goyal, 2008; Lemmon & Zender, 2010). However, studies have shown that modern capital structure theory and its empirical tests still insufficiently explain differences in firms' indebtedness (Črnigoj & Mramor, 2009). Therefore, the factors that influence how decisions regarding capital structure are made remain elusive even after decades of numerous theoretical proposals and many performed empirical tests (Frank & Goyal, 2009). Regardless of whether one takes a short-run or a long-run perspective, determinants of capital structure defined by the two prevailing theories appear to explain a relatively small fraction of the variation in leverage. For example, it was recently found that a firm's history is a more important determinant of the capital structure than a firm's characteristics that proxy the costs and benefits of debt financing. Traditionally used determinants alone (e.g. firm size, profitability, tangibility, etc.) explain approximately 16 percent of total variation, however, when including the firm's fixed effects, their explanatory power decreases to only three percent (Lemmon et al., 2008). This means that the traditional determinants explain the capital heterogeneity to a certain extent because they at least partially capture the time-invariant unobservable determinants of the capital structure.

A primary goal of capital structure research is to explain heterogeneity in corporate capital structures (Graham & Leary, 2011). Capital structure theory suggests that firms have a target leverage that is determined by various trade-offs between the costs and benefits of debt versus equity (Kayhan & Titman, 2007). In 2001, Graham and Harvey performed a survey among CFOs, and found that 37 percent of firms have a flexible target, 34 percent somewhat tight target or a range, and 10 percent a strict target (Graham & Harvey, 2001). Since only a small percent of firms uses the strict target, the theory of capital structure provides arguments that the actual capital structure would temporary deviate from the target, determined by the trade-off variables. These arguments could be the existence of information asymmetry, market inefficiencies, or positive transaction costs (Kayhan & Titman, 2007). Recent literature on capital structure (e.g. the *dynamic trade-off theory*) focuses on forces that move firms away from their target capital structure; however, these deviations are gradually eliminated. For example, it was found that a firm's history is a more important determinant of the observed capital structures than a firm's characteristics that proxy the costs and benefits of debt financing are (e.g. Lemmon et al., 2008).

One of the most influential books, explaining the characteristics of debt financing, was written by Donaldson (1961), who argued that the use of long-term debt needs to be associated only with the investments into a firm's main operations. His idea was that debt can be understood as a current use of the earnings retained in the future, and since debt has limited duration, it is often a more convenient source of financing than issuing new shares and later repurchasing them. Additionally, the process of acquiring new debt is much faster than issuing new shares, and requires much less public disclosure of information. However, Donaldson believed that the fact that the person in power is either conservative or venturesome by nature, will be one of the most important determinants of the borrowed amount of debt. He wrote that the formal reason of acquiring new debt may follow rather than precede the financial decision. More recently, Bertrand and Schoar (2003) found that CFO fixed effects are highly correlated with leverage. The fact that the CFO's personality plays an important role in capital structure decisions was corroborated by Graham, Harvey, and Puri (2011).

Through in-depth interviews of 25 firms, operating in ten different industries, Donaldson (1961) systematically presented reasons for and against the usage of long-term debt, described in accordance with the idea of the existence of the target capital structure. Donaldson defended the idea that the leverage should neither be too high, neither too low. However, it is important to recognize that firms have numerous debt policies, some very subjective, while others being more objective by nature. Donaldson thus classified firms according to their debt policies into two broad groups. Group of firms with subjective debt policies can be further divided into two subgroups. The first subgroup consists of firms that strictly avoid any long-term debt because management does not want to get any reliable appraisal of the risk, associated with it. Such firms, however, usually have enough internally generated cash for financing their operations. At the other extreme is a subgroup of firms that borrow the maximum amount that is provided by creditors. In such firms, management relies on capital markets appraisal of appropriate leverage, and would, hopefully, not provide too much debt financing. The argument goes that those who lend money are more experienced and better equipped with the models to properly assess the suitable amount of debt that should be available to a firm. In the middle is the group of firms with more objective debt policies, which rely, in addition to the external, also on the internal risk appraisal. The first subgroup of such firms uses the debt policy under which a firm can borrow the maximum available, but under the prime rate conditions. The reason is that the interest rate paid on the long-term debt became an important status symbol. The next subgroup includes firms that limit the principal amount of borrowed long-term debt to the pre-determined percentage of total firm capitalization. Closely related is also the practice to limit the maximum amount borrowed to the level, under which a firm still reaches the required earnings coverage ratio. Under both policies, management would consider any amount of debt above the limit to be too risky, regardless of the reward. Certain firms, operating in more cyclical and risky industries, exercise so-called single-project-approach or the rapid-payback-approach debt policy. In industries with high fluctuations in sales and earnings, using debt as a continuous source of financing can be unjustified. However, projects that are less risky than the general business model can be partially financed with debt. In the cyclical industries, repayment of debt in good times is desirable. From Donaldson’s debate (1961) it can be concluded that debt policies highly influence the range of the target leverage, set by the management, although sometimes without a good theoretical justification – subjective determinants could often prevail over the objective reasoning.

If an important advantage for using debt is its characteristic of limited duration and tax shield, Donaldson (1961) listed several reasons against its usage. For example, management expressed the opinion that earnings from debt savings should not be treated the same as earnings from regular operations because of debt adverse potential during the crisis period. Consequently, debt often has a negative reputation in public. The next reason can be attributed to the fact that a management follows their industry peers, who in certain periods have a negative perspective of debt – they perceive leverage to negatively affect a firm’s credit rating, shareholders’ opinion, and market perception. Next, some managers expressed a problem recognizing when the reasonable amount of debt becomes too excessive. They also noted that CFOs are often among the most conservative decision makers and prefer less debt over more. Management sometimes also considers another important aspect of debt financing – the question of control. Someone could expect that management would favor debt over equity because in case of new share issues, the proportion of voting control would change. However, one can argue that when ownership is widely dispersed, the new equity would not importantly shift the voting power. Moreover, with acquisition of new debt the financial institution that lent the money can have an important influence on a firm's internal decision-making process. Donaldson (1961) went one-step further and concluded that all arguments against the usage of debt can be reduced to one fundamental problem. That is uncertainty about the nature, amount, and time of future cash flows. He continued that all factors affecting the cash flow position must be carefully examined, with emphasis on how these factors would behave in the time of recession, the conclusion very similar to recent arguing by Kester et al. (2004). Donaldson (1961) believed that well-informed management could determine with a considerable confidence the expected impact on any future recession on the business with respect to sales and other elements of net cash flow.

From Donaldson's theoretical and empirical debate follows that there are subjective and objective determinants that influence a firm's target capital structure. Among others, two of the most important theories of modern capital structure, the *trade-off theory* and the *pecking order hypothesis*, try to determine these factors and predict the direction of relationship between individual determinant and the amount of leverage. However, it is not rare that both theories predict a different direction for the same determinant. These factors are presented and thoroughly explained in *Subchapter 2.2.2*, where explanatory variables are listed. For each factor, empirical findings on its impact on leverage are presented. The requirement for an individual factor to be included in the model is that it was found in the past research to statistically influence the target capital structure or that it has a good theoretical background that it should. Additionally, it needs to be available for sample of firms. Toy et al. (1974) argued that the variables, used for explanation of firms' debt ratios, should have a theoretical support in the financial literature, should be acknowledged by financial executives, and should be in the form that can be tested with publicly available data. It is important to stress that simply calculating a firm's average leverage during the analyzed period and taking it as the target, is, according to

Marsh (1982), extremely problematic and misleading. First, firms acquire new debt through lumpy issues over longer time intervals so even ten years would usually be too short a period of time to get a reliable estimate of the firm's target. Next, favorable short-term conditions (e.g. strong economic expansion) could give a reason to significant temporary departures from the long-term targets. Finally, the targets could change in time. Because of that, determinants that define the target leverage must be appropriately modeled and will act as a proxy for the true, but unobservable target.

2.2 Multilevel settings for explaining the corporate capital structure

It is likely that firms operating within the same industry and country are not completely independent from each other. Many researchers empirically show that both industry and country norms importantly determine firms' capital structure behavior (e.g. Frank & Goyal, 2009; Rauh & Sufi, 2010). Since I analyze firms, operating within 18 different industries and across 25 European countries, many firms are clustered within a particular group and that could materially help shape their financial behavior. Multilevel regression provides an elegant solution for the violated assumption of independent observations, because it assumes that units within the same group are more similar than they would be by chance (Gelman & Hill, 2007). Analyzing these firms as completely independent observations can result in biased model estimation. Furthermore, each firm is observed six times (from the year 2006 to the year 2011), which means that time-series dependency is present. Again, multilevel regression allows nesting repeated measurements within the firm (longitudinal study), controlling for that source of dependency. Based on the structure of the data, I use multilevel regression that accounts for cross-sectional and time-series dependence at the same time, the two forms of dependence so common in many financial studies. The hierarchy of a 4-level model is shown in *Figure 2-1*. At the lowest level, I have six firm-year observations for each firm (Level 1).[4] These firm-year observations are nested within a firm (Level 2), which is the

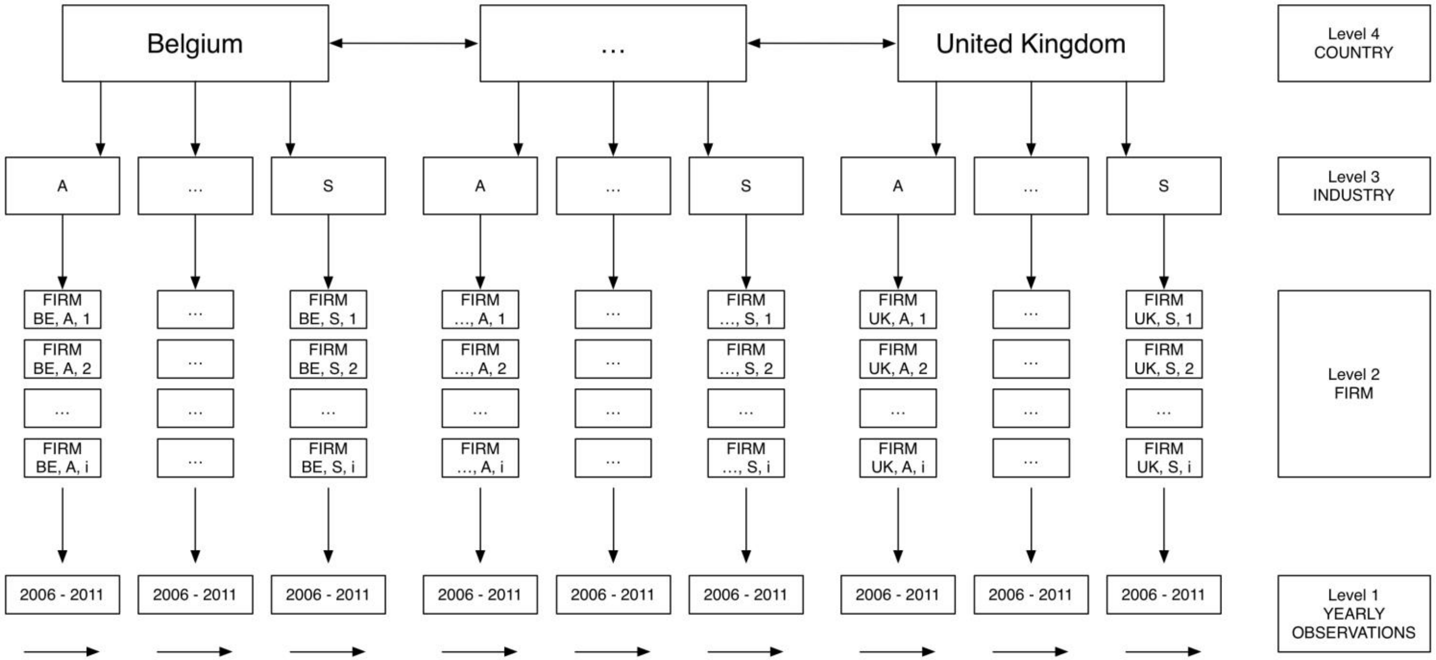
[4] Missing observations are allowed. Since data is checked for multilevel outliers and scanned with influential statistics, some observations are removed, which means that not all firms have all six year observations included.

base unit of study. Firms are further nested within 18 different industries[5] (Level 3), and these industries are nested within 25 European countries (Level 4). With the model I analyze how total financial indebtedness (i.e. *leverage*), measured at the lowest level, can be explained by predictors, measured at various levels (fixed effects), and allowing the intercept to freely vary among 3rd and 4th level units (random effects). Moreover, the model gives the estimated targets that are used in the *Subchapter 3.5* to determine the effect of capital structure on a firm's performance.

It was required that each firm-year observation has non-missing values for all explanatory variables and that leverage, expressed as a percentage of total assets, lies in the closed interval [0, 100]. To mitigate the effect of outliers and fundamental errors in the data, all continuous variables are winsorized at the upper and lower one-percentile, following similar recent empirical studies (e.g. Lemmon et al., 2008). Frank and Goyal (2008) surveyed recent studies on capital structure determinants and found that the rule-of-thumb truncation with combinations of robust regressions were also used, however, I prefer winsorizing because it does not reduce the number of observations. Further, the majority of past research on this topic was performed on the publicly traded firms. These are large firms that can be expected to behave accordingly to the financial theory and that have publicly available data. To mitigate this problem, I require that all included firms have sample average total assets exceeding €5 million[6]. This process gives me 50,584 firm-year observations, involving 8,777 firms.[7] Finally, following a common convention, the explanatory variables are measured with one-year lag (e.g. Rajan & Zingales, 1995; Lemmon et al., 2008), thus giving the firm time to adjust its capital structure and also reducing the problem of endogeneity, as argued for example by Rajan and Zingales (1995).

[5] NACE Rev. 2 sections are used.
[6] In other studies, for example in Byoun (2008), €10 million was usually the limit.
[7] These firm-year observations are checked for multivariate outliers and scanned with influential diagnostics, following the suggestions by Field (2013), Stevens (2009), Chen, Ender, and Wells, (2003), Tabachnick and Fidell (2012), and West, Welch and Galecki (2015).

Figure 2-1. *Graphical presentation of hierarchy of the model*



Source: *Own presentation.*

2.2.1 Dependent variable

The dependent variable $Leverage_{tijk}$ is defined as the percentage share of total financial debt (long- plus short-term) relative to total assets.[8] The major debate among researchers is whether market or book value should be used for the leverage calculation. The pure theory of capital structure suggests using market values. However, researchers (Toy, Stonehill, Remmers, Wright, & Beekhuisen, 1974; Stonehill, et al., 1975) found that managers tend to think in terms of book rather than market value ratios. Moreover, Lev and Pekelman (1975) argued that book value is more appropriate for modelling the target leverage, while Myers (1977) claimed that there may even be a theoretical justification for giving preference to book value, since it measures the value of assets in place, usually without the capitalized value of future growth opportunities. Myers argued that future growth opportunities are too uncertain to be financed with leverage. Marsh (1982), for example, tried to determine the target capital structure both with market and book value ratios and found no statistical difference. This finding is consistent also with Taggart (1977), who argued that there is very little to choose from between the book and market value formulation. Frank and Goyal (2009), surveying past empirical research, found that book value is often preferred because of deemed excess volatility in financial markets and, hence, that managers believe market leverage numbers are unreliable as a guide to corporate financial policy. Graham and Harvey (2001) argued that only a few managers rebalance their capital structure in response to equity market movements, the main reason being the adjustment costs. Lemmon et al. (2008) performed a study on the determinants of capital structure both on the book and market definition of leverage, however, the findings did not differ. In line with the existing research, I therefore choose to adopt the book value of equity in leverage calculation. This gives me the added advantage of including in my sample firms which are not publicly traded and therefore do not have a reliable estimate for the market value of equity.

The next concern refers to components included in the definition of leverage. In the past, researchers (Remmers, Stonehill, Wright, & Beekhuisen, 1974; Ferri &

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[8] *t* is used to index time, *i* is used to index firms, *j* is used to index industries, and *k* is used to index countries.

Jones, 1979) defined leverage as long-term debt or total financial debt relative to total assets[9], but sometimes also included accounts payable or even all liabilities (Frank & Goyal, 2009). However, accounts payable may reflect day-to-day business arrangements rather than financing considerations (Strebulaev & Yang, 2013). More recently (e.g. Lemon et al. 2008) total financial debt (long- plus short-term) is the conventional choice. I follow recent research and define leverage as shown in *Equation 2-1*.

$$Leverage_{tijk} = \left(\frac{Total\ financial\ debt_{tijk}}{Total\ assets_{tijk}}\right)100 \qquad (2\text{-}1)$$

In *Equation 2-1* $Leverage_{tijk}$ represents the dependent variable in time t for firm i, operating within industry j and within country k.

2.2.2 Predictors

Lemmon et al. (2008) estimated within- and between- firm variations of book leverage for a large sample of American firms over 20-year period. Consistent with earlier findings, the within-firm variation was approximately 50 percent smaller than between-firm variation, which means that leverage varies significantly more across firms than it varies within firms over time. Further, they decomposed the variance with ANCOVA and found that the majority of sum of squares of explained variance can be attributed to the firm fixed effects. Firm fixed effects alone explained around 60 percent of variability of leverage, while time fixed effects explained only 1 percent. Traditionally used determinates alone (e.g. firm size, profitability, tangibility, etc.) explained approximately 16 percent of total variation, however, when including firm fixed effects into the model their explanation power decreased to only 3 percent.

Frank and Goyal (2009) performed a comprehensive review of past empirical studies that analyzed the determinants with a significant power at explaining observed capital structures and that gave consistent conclusions over many tests. The six main determinants are *industry median leverage* (firms in industries in which the median firm has high leverage tend to have higher leverage), *tangibility* (firms that have more tangible assets tend to have higher leverage),

[9] However, Marsh (1982) argued that the aggregation of long- and short-term debt into a single variable leads to a loss of information.

profit (firms that have more profit tend to have lower leverage), *firm size* (firms that have larger assets or higher sales tend to have higher leverage), *market-to-book-assets ratio* (firms that have a high market to book ratio tend to have lower leverage), and *inflation* (when inflation is expected to be high, firms tend to have high leverage). Frank and Goyal (2009) found that these six determinants explain more than 27 percent of the variation in leverage. Overall, exclusion of the main determinants can have an important consequence that some other variables can become insignificant or even change the sign. However, because my sample includes many firms that are not publicly quoted, market-to-book-assets ratio is unavailable.[10] The remaining five main determinants are included in the model, together with some other determinants that were found to significantly determine the observed capital structures in the past research. As Kayo and Kimura (2011) showed, industry and country level determinants exhibit significant role in explaining capital structure heterogeneity.

2.2.2.1 Level 1 – Firm-year observations

Explanatory variables, measured at the first (firm-year) level, display meaningful time-variation, and the majority of traditional determinants of capital structure belong to this level, as described below.

Profitability. *Trade-off theory* predicts that more profitable firms have lower expected bankruptcy costs and higher tax shields and should thus be more leveraged (Frank & Goyal, 2008). Additionally, higher profits increase the agency costs of the free cash flow problem, which can successfully be mitigated with higher leverage (Jensen, 1986). However, empirical studies usually find a negative relationship between profitability and leverage (Baxter & Cragg, 1970; Martin & Scott, 1972; Taub, 1975; Titman & Wassels, 1988; Toy, Stonehill, Remmers, Wright, & Beekhuisen, 1974; Byoun, 2008). Moreover, it has been observed that the importance of profits for determining capital structure has recently decreased. According to Frank and Goyal (2009), equity markets are becoming more willing to fund currently unprofitable firms with good growth prospects. It can be argued that empirical findings are consistent with the

[10] Frank and Goyal (2009) argued that in case of book value defined leverage, market-to-book-assets ratio can be omitted without significant consequences.

pecking order hypothesis, while inconsistent with the *trade-off theory*. However, Frank and Goyal (2008) argued that profitability can be understood as a proxy for growth opportunities and in that case, the negative sign is consistent with the predictions of the *trade-off theory*. Moreover, the *dynamic trade-off theory* acknowledges that leverage and profitability can be negatively correlated due to various market frictions (Strebulaev, 2007). One of the possible explanations can be found in the argument that firms passively accumulate profits and thus more profitable firms need less external financing (Kayhan & Titman, 2007). Another argument stipulates that profitable firms have more investment opportunities. For such firms it makes sense to retain more earnings because investors will be unable to earn such high profits elsewhere. *Trade-off theory* thus offers ambiguous predictions regarding leverage and profitability. Based on previous empirical research I expect to find a negative relationship. The definition of *Profitability,* used also by Byoun (2008), is given in *Equation 2-2*.

$$Profitability_{tijk} = \left(\frac{EBIT_{tijk}}{Total\ assets_{tijk}}\right)100 \tag{2-2}$$

Firm size. Firm size significantly affects capital structure, as argued, for example, by Gupta (1969), Lev (1969), Baxter and Cragg (1970), Martin and Scott (1972), Ferri and Jones (1979), and Frank and Goyal (2008). *Trade-off theory* predicts that larger firms will have more leverage because they are more diversified, have lower default risk and are more mature. Consequently, they have a better reputation in debt markets and face lower agency costs of debt. *Trade-off theory* thus predicts that firm size positively affects leverage (Frank & Goyal, 2008). Graham and Leary (2011) surveyed recent empirical studies and found that highly leveraged firms are significantly larger. The main argument goes that larger firms have lower probability of default and, consequently, a higher target debt ratio.

On the other hand, it could be argued that larger firms face lower adverse selection and consequently have easier access to external equity. However, larger firms have more assets and thus adverse selection might be more important. The *pecking order hypothesis* therefore predicts an ambiguous effect of size on leverage. Baxter and Cragg (1970), Martin and Scott (1972), and Taub (1975) performed empirical analyses where they found that smaller firms are more likely to issue equity than debt, which goes in line with *trade-off theory*. However, Toy et al. (1974) argued that it is highly inconclusive how firm size affects the target capital structure. More recently, Kortweg (2010) argued that smaller firms have higher optimal debt ratio. Although different theories propose different predictions about the relationship between firm size and leverage, the majority of past research (e.g. Lemmon et al., 2008; Byoun, 2008) show that larger firms are more heavily leveraged so I expect a positive relation between firm size and leverage. I choose total assets as an indicator of firm size because it is a more stable indicator compared to total sales, especially in times of crisis. Due to distributional properties of total assets, I log the chosen indicator and define *Firm size* as shown in *Equation 2-3*.

$$Firm\ size_{tijk} = log_{10}(Total\ assets_{tijk}) \tag{2-3}$$

Firm growth. Fast growth increases the costs of financial distress, reduces the free cash flow problem, and increases debt-related agency problems such as underinvestment or asset substitution (Jensen & Meckling, 1976). *Trade-off* and other agency costs theories thus predict that firms with faster growth will be less indebted (Frank & Goyal, 2009). This is in line with Martin and Scott (1972), who showed with multivariate discriminant analysis that firms with more rapid short-term sales growth are less likely to issue debt. On the other hand, Toy et al. (1974) documented that firms with high assets growth rate have higher debt ratios. This is consistent with the *pecking order hypothesis*, which predicts that firms with fast growth would accumulate more debt over time, because investments cannot be all financed solely with internally generated funds. However, the majority of empirical research shows that firms with higher growth are less indebted (e.g. Bradley et al., 1984; Smith & Watts, 1992; Rajan & Zingales, 1995; Barclay, Smith, & Watts, 1995; Frank & Goyal, 2009; Barclay, Morellec, & Smith, 2013). Accordingly, I predict a negative relation and define *Firm growth* as shown in *Equation 2-4.*

$$Firm\ growth_{tijk} = \left(\frac{Total\ assets_{(t+1)ijk}}{Total\ assets_{tijk}} - 1\right) 100 \tag{2-4}$$

Assets composition. Firms usually try to match the maturity of assets with maturity of liabilities, which means that fixed assets should be financed with long-term debt and shareholders' equity (Marsh, 1982). Many researchers (Baxter & Cragg, 1970; Martin & Scott, 1972; Taub, 1975) found the positive correlation between high proportion of fixed assets and new debt issues. Similarly, high fixed assets turnover can lead to the high use of debt (Gupta, 1969). More recently, scholars recognized the importance of tangible assets as a determinant of capital structure (e.g. Harris & Raviv, 1990; Stultz, 1990; Hirshleifer & Thakor, 1992; Byoun, 2008). Kortweg (2010) showed that leverage is positively related to the proportion of tangible assets. Highly tangible assets, such as property, plant, and equipment, lower the expected costs of financial distress because they are easier to value than intangible assets, which means that *trade-off theory* predicts a positive relationship. Additionally, as argued by Frank and Goyal (2009), tangibility reduces the problem of assets substitution. On the other hand, the *pecking order hypothesis* concentrates on the relation between information asymmetry and tangibility. This theory predicts that higher tangibility reduces information asymmetry and makes issuing equity less costly. This consequently results in lower debt ratios (Harris & Raviv, 1991). I define *Tangibility* as shown in *Equation 2-5*, and predict a positive relation.

$$Tangibility_{tijk} = \left(\frac{Tangible\ assets_{tijk}}{Total\ assets_{tijk}}\right)100 \tag{2-5}$$

2.2.2.2 Level 2 – Firm

The second level includes variables that are time-invariant – the permanent characteristics of a firm. Lemmon et al. (2008) showed that traditionally used determinants alone (e.g. firm size, profitability, tangibility) explain approximately 16 percent of total variation of leverage, however, upon including firm fixed effects into the model, their explanatory power decreased to only 3 percent. This strongly suggests that traditional determinants explain the capital structure well because they at least partially capture the time-invariant unobservable determinants of capital structure.

Probability of financial distress. Many researchers confirmed that cross-sectional variation in capital structures can be explained by differences in probability of a firm's risk of financial distress (e.g. Gupta, 1969; Lev, 1969; Scott, 1972; Toy et al., 1974; Stonehill et al., 1975; Brealey, Hodges, & Capron, 1976; Briscoe & Hawke, 1976; Carleton & Silberman, 1977; Ferri & Jones, 1979; Flath & Knoeber, 1980). There have been numerous attempts in the past to proxy financial distress with evaluation of the costs of bankruptcy. There are two types of such costs: direct and indirect costs (Warner, 1977). Direct costs include lawyers', accountants' and other professionals' fees, and the value of managerial time spent in administering the process of bankruptcy. One of the indirect costs is loss in sales, because potential buyers of the firm's product perceive the default to be likely, which results in lower profits. Another type of indirect costs is the inability of the firm to obtain loan or to issue securities except under very unfavorable terms. Kim (1978), on the other hand, classified bankruptcy costs into three categories. First, the shortfall arising from the liquidation of physical assets below their economic value, second, fees and other compensations to third parties included in the process of liquidation or bankruptcy, and third, tax court's refusal to grant tax credits for the tax losses of a bankrupt firm. Because bankruptcy costs are practically impossible to measure ex ante, researchers used different surrogates for modeling it. Castanias (1983) tested *trade-off theory* by studying the cross-sectional relationship between probability of failure and leverage. Theory predicts that this relationship will be negative. As a proxy for bankruptcy costs, he used historical failure rates across industries and with the use of Kendall and Pearson correlation coefficients proved a negative relationship between failure rates and a firm's indebtedness. He concluded that ex ante default costs are large enough to force a firm to use the target capital structure. Another important type of bankruptcy costs are costs borne by employees, who lose their job (Berk, Stanton, & Zechner, 2010). This indirect cost of financial distress is ultimately borne by the firm through higher wages and thus discourages the use of debt in a trade-off sense. Authors argued that human cost is an example of indirect bankruptcy cost, which is large enough to offset the benefits of debt.

Ferri and Jones (1979) argued that the variability of a firm's income is the main factor in ex ante estimates of the firm's ability to meet fixed charges, and suggested the degree of operating leverage as an appropriate measure. Similarly, Marsh (1982) proposed to use the standard deviation of EBIT, scaled by total firm's sales. Gupta (1969) showed that uncertainty, measured with the instability of sales, negatively affects leverage. The same was found by Martin and Scott (1972). Toy et al. (1974) argued that firms with higher variability of earnings should be less indebted because of increased probability of bankruptcy and limits imposed by lenders. Also shown by Brennan and Schwartz (1978), firms with higher business risk will have, all else equal, lower optimal leverage. More recently, Kortweg (2010) argued that the higher is earnings variability, the higher is the probability for financial distress. Lemmon et al. (2008) suggested modeling that risk using the standard deviation of operating income. I proxy the probability of financial distress as shown in *Equation 2-6* and expect to find a negative relationship.

$$Fin.distress_{ijk} = \left(\frac{SD\ (EBIT_{tijk})}{Average\ (Total\ assets_{tijk})}\right)100 \tag{2-6}$$

Legal status of the company. Public firms are more profitable, invest more, and use more equity financing, according to Frank and Goyal (2008). I expect that public firms will have, on average, lower leverage and, thus, I define a public firm dummy variable as shown in *Equation 2-7*.[11]

$$D_{PUBLIC} = \begin{cases} Public\ firm = 1 \\ Otherwise = 0 \end{cases} \tag{2-7}$$

Firms producing unique and durable goods. Shareholder co-investment theory (Titman, 1984; Titman & Wassels, 1988) predicts that firms which produce unique products (e.g. durable products) should be less indebted. The indirect costs of distress can be high when such distress would bring difficulties for its customers (they are hesitant to purchase from a firm that might default and not offer service for its products) or suppliers (they can stop supplying to a firm in or near distress). These issues are heightened for durable goods producers because for such products future service is important (Graham & Leary, 2011). Besides, firms producing unique durable products have more specialized labor and uniqueness of assets, which results in increased financial costs of distress. The uniqueness of assets usually results from larger expenditures on selling, general and administrative expenses or high research and development costs. The selection of industry (NACE Rev. 2: Division 26–32 (Eurostat, 2016)) follows the suggestion by Banerjee, Sudipto, and Kim (2008), and Frank and Goyal (2009). Therefore firms operating in these industries are expected to be less indebted to decrease the probability of bankruptcy. They are coded with a dummy variable of 1, otherwise 0, as shown in *Equation 2-8*.

$$D_{UNIQUE\ PRODUCTS} = \begin{cases} Unique\ products = 1 \\ Otherwise = 0 \end{cases} \tag{2-8}$$

[11] Previous empirical studies are usually performed on public firms only, because private firms have limited or no available data (e.g. market-to-book ratio). Because I use book-defined leverage, both types of firms are admitted.

2.2.2.3 Level 3 – Industry

Industry characteristics importantly determine firm’s operations (Kayo & Kimura, 2011). For example, Rauh and Sufi (2010) found that the degree of asset tangibility highly correlates across firms within the same industry. Consequently, firms operating within the same industry will have similar amount of business risk, which importantly determines the amount of debt the capital markets will provide (Ferri & Jones, 1979). As shown by Brennan and Schwartz (1978), firms with higher business risk will have, all else equal, lower optimal leverage. Gupta (1969) emphasized that leverage is a function of multivariates that have different importance in different industries. Industry classification is thus an important factor that will influence how determinants affect the target capital structure. The within-industry forces, which are likely to affect firms’ financing decisions, could be in the form of product market interactions, nature of the competition, the types of assets used in the production process, business risk, state of technology, or regulations (Frank & Goyal, 2009).

Schwartz and Aronson (1967), Scott (1972), Bowen, Daley, and Huber (1982), and Bradley et al. (1984) found that firms within an industry are more homogenous compared to firms from different industries. Additionally, industries tend to retain relative leverage ratio ranking over time. This important finding led to the conclusion that each industry has a unique target capital structure. Schwartz and Aronson (1967) argued that if the target capital structure does not exist, then theoretically there should be no recognizable patterns of financial structures among industries. Bradley et al. (1984) surveyed 851 firms from 25 different industries and calculated the average 20-year ratio (1962–1981) between book value of long-term debt and the sum of book value of long term debt and the market value of equity. With the use of ANOVA they found significant differences among leverage ratios and concluded that industry classification alone could explain up to 54 percent of total leverage variability. On the other hand, Remmers et al. (1974), Ferri and Jones (1979), and Chaplinsky (1984) did not find enough evidence to support the differences in capital structures among industries.

Bowen et al. (1982) summarized that previous empirical studies showed conflicting conclusions on the existence of differences in target capital structure among industries. They proposed three main hypotheses, which would determine the importance of industry classifications:

> H1: Firms in different industries have systematically different capital structure.
>
> H2: The relative rankings of mean industry financial structures across time are stable.
>
> H3: The leverage of firms within an industry tends to converge to the mean industry leverage.

When testing the first hypothesis, Schwartz and Aronson (1967), Scott (1972), and Scott and Martin (1975) found statistical differences among industries. The study by Scott and Martin (1975) is especially interesting, because both parametric and non-parametric statistical techniques were used and the analysis was controlled by firm size through the analysis of covariance. Remmers et al. (1974), and Belkaoui (1975), on the other hand, did not find statistical differences among industries. Bowen et al. (1982) performed an analysis of variance for nine different industries and calculated ω^2, which measures the percentage of variance of firms' leverage explained by the knowledge of industry classification. The analysis was performed for 1951–1969 for a sample of American firms and results were highly statistically significant. The average ω^2-statistics was 0.275. They continued with pairwise tests of arithmetic means with the least significant difference test and got a large number of pairwise comparisons to be significant. The second hypothesis was usually tested with the help of Spearman rank correlation coefficient and the Kendall-W coefficient of concordance. Bowen et al. (1982) found that relative rankings of average industry capital structures across time are stable. Similarly, Schwartz and Aronson (1967) argued that the leverage structure of industries does not change much. When testing the third hypothesis, Bowen et al. (1982) performed Fisher exact probability test. This is a non-parametric test that gives the probability of the actual or more extreme configuration under the null hypothesis if no directionality is observed. Over the 5- and 10-year period, authors proved the existence of tendency movements towards the industry median indebtedness. Industry median indebtedness is thus an important determinant of firm's capital structure. Scott (1972) critically reexamined the empirical study of Schwartz and Aronson (1967), who claimed that leverage significantly differs among industries and that financial structures within the industries remain relatively stable over time. Scott selected a sample of 77 firms from 12 unregulated industries. The time span of the research was 10 years (1959–1968). With the use of ANOVA, author proved the statistical difference in at least one industry at a very high level of significance. In order to prove differences more thoroughly, Scott (1972) used multiple comparison test. For the year 1968 he showed that 62.5 percent of all possible pairs among 12 industries were statistically significant at 5 percent level, from which it follows that the differences in financial structures are quite persistent.

I want to verify if there are statistically significant differences in firms' indebtedness across industries during the period 2006–2011. Past research on differences in the capital structure between industries and countries was usually performed with one-way ANOVA, analyzing if the industry or country factor statistically explains the difference in average indebtedness. I first try two-way ANOVA, including both factors at the same time, and find statistically significant results for both. Moreover, the cross-product effect between both factors was especially strong, meaning that the industries affect average indebtedness differently in different countries. However, because the assumptions of normality of the dependent variable and equality of variances across groups were violated, I decide to use the non-parametric version of one-way ANOVA – the Kruskal-Wallis test. Because the Kruskal-Wallis test assumes that observations in each group come from the population with the same shape of distribution, I additionally perform Mood's median test, which, instead of analyzing ranks, tests if samples are drawn from a population with the same median, and is robust to different distributional shapes (Field, 2013). Both tests are performed on the share of the long-term debt relative to total assets, on the share of the total financial debt (long- and short-term debt) relative to total assets, and on the share of the total debt (long- and short-term debt & accounts payable) relative to total assets, using industry as a grouping variable. Tests are performed for each year separately. In the *Table 2-1* results are shown.

Table 2-1. *Testing differences in indebtedness – grouping variable is industry*

		Kruskal-Wallis test			**Mood's median test**		
		Long-term debt relative to TA	Long- and short-term debt relative to TA	Long- and short-term debt & payables relative to TA	Long-term debt relative to TA	Long- and short-term debt relative to TA	Long- and short-term debt & payables relative to TA
Grouping by industry (df = 17)	2006	$\chi^2 = 1102.7$	$\chi^2 = 795.2$	$\chi^2 = 621.2$	$\chi^2 = 587.5$	$\chi^2 = 476.9$	$\chi^2 = 502.3$
	2007	$\chi^2 = 1147.9$	$\chi^2 = 817.3$	$\chi^2 = 639.3$	$\chi^2 = 623.9$	$\chi^2 = 530.6$	$\chi^2 = 502.9$
	2008	$\chi^2 = 1112.6$	$\chi^2 = 759.6$	$\chi^2 = 587.6$	$\chi^2 = 583.1$	$\chi^2 = 510.7$	$\chi^2 = 467.2$
	2009	$\chi^2 = 1138.0$	$\chi^2 = 827.1$	$\chi^2 = 619.0$	$\chi^2 = 588.0$	$\chi^2 = 526.9$	$\chi^2 = 514.6$
	2010	$\chi^2 = 1134.1$	$\chi^2 = 822.7$	$\chi^2 = 637.7$	$\chi^2 = 599.9$	$\chi^2 = 520.5$	$\chi^2 = 527.0$
	2011	$\chi^2 = 1127.1$	$\chi^2 = 780.9$	$\chi^2 = 609.3$	$\chi^2 = 581.3$	$\chi^2 = 485.6$	$\chi^2 = 510.3$

Note: All differences are statistically significant at *p*-value below 0.001, sample size is 8,777 firms.

Source: Bureau van Dijk, *Amadeus database*, 2013.

In compliance with the results obtained with two-way ANOVA, non-parametric tests show that industry classification has determining power for analyzing differences in the average and median indebtedness. Because all significance levels are very high, I can conclude that during the period 2006–2011 there were statistical differences in the average and median indebtedness between European firms operating in different industries. This provides additional support for using multilevel regression.

Frank and Goyal (2009) argued that empirical studies show that firms converge to industry norms. Industry leverage is thus a powerful predictor because it reflects a number of otherwise omitted common factors that influence a firm's capital structure (Byoun, 2008). More recently, Leary and Roberts (2014) found evidence that industry leverage is that important determinant because firms are directly influenced by the financing choices of their peers. For example, Hovakimian et al. (2001) provided evidence that firms actively adjust their indebtedness toward the target, expressed as industry median debt ratio. The same was found by Gilson (1997), Hull (1999), Facio and Masulis (2005), and Flannery and Rangan (2006). MacKay and Phillips (2005) provided a comprehensive review of industry effects on leverage and showed that capital structure, technology, and risk are jointly determined within industries. There is, according to researchers, a strong interdependence of firms operating within the same industry. With multilevel regression I control for similarity of firms operating within the same industry on the one hand, and for heterogeneity among them, on the other. As will be shown later, intraclass correlation between firms (i.e. a measure of similarity between two randomly selected units, clustered within the same group), operating within the same industry, is far above permissible 10 percent. With the random intercept at industry level, differences in industry indebtedness are effectively modeled, substituting the commonly used *Industry median leverage* as an explanatory variable of capital structure research.

2.2.2.4 Level 4 – Country

Stonehill and Stitzel (1969) showed that large cross-country differences exist in indebtedness of the same industry and they concluded that debt ratios are more clustered by country than they are by industry. Reasons for such national clustering can be found in cultural, institutional, and accounting differences. Country norms could therefore be more important than industry norms. Toy et al. (1974) argued that international monetary variables (e.g. the need for foreign borrowing, exchange rate risk, repatriation of capital), capital-market conditions, the role of government in case of bankruptcy, and the historical development of debt ratios should importantly influence the target capital structure. It is thus important to incorporate into the model the fact that firms operating within the same country are not independent. This is done through the fourth level of multilevel regression.

Table 2-2. *Testing differences in indebtedness – grouping variable is country*

		Kruskal-Wallis test			**Mood's median test**		
		Long-term debt relative to TA	Long- and short-term debt relative to TA	Long- and short-term debt & payables relative to TA	Long-term debt relative to TA	Long- and short-term debt relative to TA	Long- and short-term debt & payables relative to TA
Grouping by country (df = 24)	2006	$\chi^2 = 1176.9$	$\chi^2 = 1108.4$	$\chi^2 = 1268.2$	$\chi^2 = 803.5$	$\chi^2 = 718.5$	$\chi^2 = 804.7$
	2007	$\chi^2 = 1018.1$	$\chi^2 = 1022.4$	$\chi^2 = 1360.8$	$\chi^2 = 677.6$	$\chi^2 = 707.6$	$\chi^2 = 956.6$
	2008	$\chi^2 = 1027.6$	$\chi^2 = 1016.7$	$\chi^2 = 1149.0$	$\chi^2 = 699.1$	$\chi^2 = 738.6$	$\chi^2 = 778.1$
	2009	$\chi^2 = 1030.2$	$\chi^2 = 959.9$	$\chi^2 = 1192.9$	$\chi^2 = 750.4$	$\chi^2 = 736.0$	$\chi^2 = 837.6$
	2010	$\chi^2 = 1066.1$	$\chi^2 = 1046.0$	$\chi^2 = 1265.9$	$\chi^2 = 773.7$	$\chi^2 = 761.7$	$\chi^2 = 865.5$
	2011	$\chi^2 = 1064.2$	$\chi^2 = 1035.9$	$\chi^2 = 1253.3$	$\chi^2 = 778.9$	$\chi^2 = 754.8$	$\chi^2 = 852.3$

Note: All differences are statistically significant at *p*-value below 0.001, sample size is 8,777 firms.

Source: Bureau van Dijk, *Amadeus database*, 2013.

As in the previous subchapter, I verify whether there are statistically significant differences in firms' indebtedness across European countries. In *Table 2-2* results are shown.

Since all *p*-values are very low, I can conclude that during the period 2006–2011 there were statistical differences in average and median indebtedness between the firms operating in different European countries. In addition to using the random intercept at the Level 4, three predictors are used.

GDP growth. Trade-off theory predicts that during expansions expected bankruptcy costs are reduced and firms borrow more. On the other hand, the *pecking order hypothesis* predicts that during expansions firms generate more internal funds and have lower need for new borrowing. GDP growth is also a good control variable for recession, as suggested by Frank and Goyal (2009). I include in the model variable (real) $GDPgrowth_{tk}$.

Inflation. Since the real value of interest tax deductions on debt is higher in times of high inflation (Taggart, 1985), *trade-off theory* predicts that leverage is positively related to inflation. A positive relation can also arise when management is timing debt issues. This means that debt is issued when expected inflation is high relative to the current interest rates (Frank & Goyal, 2008). I use the official inflation rate ($Inflation_{tk}$), expecting a positive relation.

Tax rate. In 1960 researchers started debating which factors determine the target capital structure. At that time, the majority agreed that taxes were an important determinant (Marsh, 1982; Taub, 1975). *Trade-off theory* predicts that firms will use more debt when taxes are high to take advantage of the interest tax shield. Increase in the tax rate should therefore increase the desired debt-equity ratio because of the tax advantage of debt, or as argued by Scott (1976), the optimal level of debt is an increasing function of the corporate tax rate. However, Marsh (1982) believed that modeling tax effect as a determinant of target capital structure is challenging. The problem is that in a given year, firms in the same country usually have the same taxation, so the cross-sectional effect cannot be determined. The tax rate can therefore be modeled only in a time-series analysis, under the condition that the tax regime changed during the analyzed period. Because my sample includes firms from 25 European countries with different corporate tax rates, I seek to assess whether the statuary corporate tax rate[12] (as suggested by Graham (1996)) has significant power in explaining observed capital structures ($Tax\ rate_k$). I expect to find a positive relation.

2.3 Multilevel model for explaining the corporate capital structure

The general model for explaining capital structure heterogeneity is written in *Equation 2-9*.

$$
\begin{aligned}
Leverage_{tijk} = {} & \left.\beta_0 X^{(0)}_{(t-1)ijk} + \beta_1 X^{(1)}_{(t-1)ijk} + \beta_2 X^{(2)}_{(t-1)ijk} + \cdots + \beta_{p-1} X^{(p-1)}_{(t-1)ijk} + \right\} fixed\ effects \\
& \left. u_{0\,k} Z^{(0)}_{(t-1)ijk} + u_{1\,k} Z^{(1)}_{(t-1)ijk} + \cdots + u_{q-1\,k} Z^{(q-1)}_{(t-1)ijk} + r_{0\,j|k} W^{(0)}_{(t-1)ijk} + r_{1\,j|k} W^{(1)}_{(t-1)ijk} + \cdots + r_{r-1\,j|k} W^{(r-1)}_{(t-1)ijk} + \varepsilon_{tijk} \right\} random\ effects
\end{aligned}
\tag{2-9}
$$

In *Equation 2-9*, t indexes longitudinal observations of the dependent variable for a given firm (*t = 2007, 2008, 2009, 2010, 2011, 2012*), i indexes the i-th firm ($i = 1, 2, \ldots, m_{jk}$), j indexes industries ($j = 1, 2, \ldots, 18$) and k indexes countries ($k = 1, 2, \ldots, 25$). β_0 is the regression intercept, $\beta_1, \ldots, \beta_{p-1}$ is a set of partial regression coefficients – fixed effects, and $X^{(0)}$, $X^{(1)}, \ldots, X^{(p-1)}$ is a set of p covariates, lagged for one year. Articles, published more recently (e.g. Lemmon et al., 2008; Frank & Goyal, 2009), used 1-year lag for incorporating the fact that firm needs some time to incorporate new information and adjust its leverage accordingly.[13] p covariates are explanatory variables on one of four levels. Explanatory variables on the first level are time-varying characteristics of an individual firm (e.g. share of tangible assets in time t), explanatory variables on the second level are time-invariant characteristics of an individual firm (e.g.

[12] I am aware that the statutory (nominal) tax rate and the effective tax rate (the amount of taxes actually paid by a firm) can be quite different; however, I am unable to obtain the effective rate. Additionally, Huizinga, Leaven, and Nicodeme (2008) made a research on 32 European countries during the period from 1994 to 2003 and found that larger firms face international tax incentives, while my analysis ignores this possibility.

[13] I additionally perform the multilevel model with 2- and 3-year lag, and find that results are robust. However, because incorporating higher order lags results in fewer longitudinal observations, 1-year lag is used, which goes in line with a contemporary research.

legal status of the firm), and explanatory variables on the fourth level are country characteristics (e.g. GDP growth in time *t*). Variables on higher levels can be either time-varying or time-invariant.

The second set in *Equation 2-9* contains q covariates, $Z^{(0)}, \dots, Z^{(q-1)}$, associated with random effects $u_{0\,k}, \dots, u_{q-1\,k}$, that are specific to country k – random effects on the fourth level. The third set contains r covariates, $W^{(0)}, \dots, W^{(r-1)}$, associated with the random effects $r_{0\,j|k}, \dots, r_{r-1\,j|k}$, that are specific to industry *j* in country *k* ($j|k$) – random effects on the third level. Finally ε_{tijk} is a residual. There are no random effects on the second-level because estimating random effects on the firm level is computationally infeasible, due to large sample size. In case that only intercept is allowed to be random across industries and countries, the random part of the model simplifies into $u_{0\,k} + r_{0\,j|k} + \varepsilon_{tijk}$. Model can also be written in a matrix form, as shown in *Equation 2-10*.

$$\begin{aligned} \boldsymbol{Leverage_{ijk}} &= \boldsymbol{X_{ijk}\beta} + \boldsymbol{Z_{ijk}u_k} + \boldsymbol{W_{ijk}r_{j|k}} + \boldsymbol{\varepsilon_{ijk}} \\ &\boldsymbol{u_k} \sim N(\boldsymbol{0}, \boldsymbol{D_k}) \\ &\boldsymbol{r_{j|k}} \sim N(\boldsymbol{0}, \boldsymbol{D_{j|k}}) \\ &\boldsymbol{\varepsilon_{ijk}} \sim N(\boldsymbol{0}, \boldsymbol{R_{ijk}}) \end{aligned} \tag{2-10}$$

In *Equation 2-10*, dependent variable represents a vector of continuous responses for the *i*-th firm, as shown in *Equation 2-11*.

$$\boldsymbol{Leverage_{ijk}} = \begin{pmatrix} Leverage_{2006ijk} \\ Leverage_{2007ijk} \\ \vdots \\ Leverage_{2011ijk} \end{pmatrix} \tag{2-11}$$

$\boldsymbol{X_{ijk}}$ is $n_i \times p$ design matrix, which represents the known values of the *p* covariates for each of the n_i observations, collected on the *i*-th firm. This is written in *Equation 2-12*.

$$\boldsymbol{X_{ijk}} = \begin{pmatrix} 1 & X^{(1)}_{2005ijk} & \cdots & X^{(p-1)}_{2005ijk} \\ 1 & X^{(1)}_{2006ijk} & \cdots & X^{(p-1)}_{2006ijk} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & X^{(1)}_{2010ijk} & \cdots & X^{(p-1)}_{2010ijk} \end{pmatrix} \tag{2-12}$$

The first column is set to 1 for all observations, representing the regression constant. Similarly, time-invariant explanatory variables (e.g. firm specific characteristics) also have equal values in the entire column. The $\boldsymbol{\beta}$ is a vector of regression constant and *p-1* unknown partial regression coefficients (fixed effect parameters), associated with the *p* covariates in $\boldsymbol{X_{ijk}}$ matrix, as shown in *Equation 2-13*.

$$\boldsymbol{\beta} = \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_{p-1} \end{pmatrix} \tag{2-13}$$

The next term in *Equation 2-10*, $\boldsymbol{Z_{ijk}}$, which is associated with random effects, represents the known values of the *q* covariates for the *i*-th firm. This matrix is very much like the $\boldsymbol{X_{ijk}}$, however, it usually has a lower number of columns because not all covariates are allowed to have a random effect. Very often only intercept is allowed to vary randomly from subject to subject. In that case, $\boldsymbol{Z_{ijk}}$ would consist of one column of 1's. The matrix is written in *Equation 2-14.*

$$\boldsymbol{Z_{ijk}} = \begin{pmatrix} 1 & Z^{(1)}_{2005ijk} & \cdots & Z^{(q-1)}_{2005ijk} \\ 1 & Z^{(1)}_{2006ijk} & \cdots & Z^{(q-1)}_{2006ijk} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & Z^{(1)}_{2010ijk} & \cdots & Z^{(q-1)}_{2010ijk} \end{pmatrix} \tag{2-14}$$

The $\boldsymbol{u_k}$ is a vector of *q* random effects of the *k*-th country, as written in *Equation 2-15*.

$$\boldsymbol{u_k} = \begin{pmatrix} u_{o\ k} \\ u_{1\ k} \\ \vdots \\ u_{q-1\ k} \end{pmatrix} \tag{2-15}$$

By definition, random effects are random variables. I assume that the *q* random effects in the $\boldsymbol{u_k}$ vector follow a multivariate normal distribution, with mean vector $\mathbf{0}$ and a variance-covariance matrix denoted by $\boldsymbol{D_k}$. This can be written as $\boldsymbol{u_k} \sim N(\mathbf{0}, \boldsymbol{D_k})$.

In $\boldsymbol{D_k}$ matrix, elements along the main diagonal represent the variances of each random effect in $\boldsymbol{u_k}$, and off-diagonal elements represent the covariances between pairs of corresponding random effects. Because there are *q* random effects in the model associated with the *k*-th country, $\boldsymbol{D_k}$ is a $q \times q$ matrix that is symmetric and positive definite, as written in *Equation 2-16*.

$$\boldsymbol{D_k} = Var(\boldsymbol{u_k})$$
$$= \begin{pmatrix} Var(u_{o\,k}) & cov(u_{o\,k}, u_{1\,k}) & \cdots & cov(u_{o\,k}, u_{q-1\,k}) \\ cov(u_{o\,k}, u_{1\,k}) & Var(u_{1\,k}) & \cdots & cov(u_{1\,k}, u_{q-1\,k}) \\ \vdots & \vdots & \ddots & \vdots \\ cov(u_{o\,k}, u_{q-1\,k}) & cov(u_{1\,k}, u_{q-1\,k}) & \cdots & Var(u_{q-1\,k}) \end{pmatrix} \qquad (2\text{-}16)$$

Elements of random effects on the fourth level, $\boldsymbol{Z_{ijk}}$, $\boldsymbol{u_k}$ and $\boldsymbol{D_k}$, can analogously be applied to the elements of random effects on the third level, $\boldsymbol{W_{ijk}}$, $\boldsymbol{r_{j|k}}$ and $\boldsymbol{D_{j|k}}$, therefore they will not be repeated. Different covariance structures can be applied for the $\boldsymbol{D}$ matrix. The elements of such matrix are usually denoted with a vector $\boldsymbol{\theta_D}$. The covariance structure with no constraints on the values of elements is referred to as an unstructured $\boldsymbol{D}$ matrix, which is the preferred choice for random coefficient models. Another often used covariance structure is variance component (or diagonal) structure, in which each random effect in $\boldsymbol{u}$ has its own variance, while all covariances are set to zero.

The last element of *Equation 2-10*, $\boldsymbol{\varepsilon_{ijk}}$, is a vector of n_i residuals, with each element denoting the residual associated with an observed response at time t for the *i*-th firm, as shown in *Equation 2-17*.

$$\boldsymbol{\varepsilon_{ijk}} = \begin{pmatrix} \varepsilon_{2006\,ijk} \\ \varepsilon_{2007\,ijk} \\ \vdots \\ \varepsilon_{2011\,ijk} \end{pmatrix} \qquad (2\text{-}17)$$

Contrary to the assumption of the standard OLS regression, multilevel regression assumes that residuals can be dependent. This dependency is controlled through different covariance structures of residuals. It is assumed that a vector of residuals follows a multivariate normal distribution with a mean vector $\boldsymbol{0}$ and a positive definite symmetric covariance matrix $\boldsymbol{R_{ijk}}$. This can be written as $\boldsymbol{\varepsilon_{ijk}} \sim N(\boldsymbol{0}, \boldsymbol{R_{ijk}})$. $\boldsymbol{R_{ijk}}$ is presented in *Equation 2-18*.

$$\boldsymbol{R_{ijk}} = Var(\boldsymbol{\varepsilon_{ijk}})$$
$$= \begin{pmatrix} Var(\varepsilon_{2006\,ijk}) & cov(\varepsilon_{06\,ijk}, \varepsilon_{07\,ijk}) & \cdots & cov(\varepsilon_{06\,ijk}, \varepsilon_{11\,ijk}) \\ cov(\varepsilon_{06\,ijk}, \varepsilon_{07\,ijk}) & Var(\varepsilon_{2007\,ijk}) & \cdots & cov(\varepsilon_{07\,ijk}, \varepsilon_{11\,ijk}) \\ \vdots & \vdots & \ddots & \vdots \\ cov(\varepsilon_{06\,ijk}, \varepsilon_{11\,ijk}) & cov(\varepsilon_{07\,ijk}, \varepsilon_{11\,ijk}) & \cdots & Var(\varepsilon_{2011\,ijk}) \end{pmatrix} \qquad (2\text{-}18)$$

There are different possibilities for modeling covariance structure of the $\boldsymbol{R_{ijk}}$ matrix. The elements of such matrix are usually denoted with a vector $\boldsymbol{\theta_R}$. The simplest covariance matrix is the diagonal structure, in which the residuals associated with observations on the same subject are assumed to be uncorrelated and to have equal variance. Another possibility is the compound symmetry covariance structure, which assumes constant covariance and constant variance term. The structure is often used when an assumption of equal correlation of residuals is plausible. The covariance structures, used in my models, are first-order autoregressive structure (AR(1)), and unstructured correlation structure (UNR). The AR(1) structure can be written as in *Equation 2-19*.

$$\boldsymbol{R_{ijk}} = Var(\boldsymbol{\varepsilon_{ijk}}) = \begin{pmatrix} \sigma^2 & \sigma^2\rho & \cdots & \sigma^2\rho^{n_i-1} \\ \sigma^2\rho & \sigma^2 & \cdots & \sigma^2\rho^{n_i-2} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma^2\rho^{n_i-1} & \sigma^2\rho^{n_i-2} & \cdots & \sigma^2 \end{pmatrix} \tag{2-19}$$

The AR(1) covariance structure only has two parameters so it can be parsimoniously written as in *Equation 2-20*.

$$\boldsymbol{\theta_R} = \begin{pmatrix} \sigma^2 \\ \rho \end{pmatrix} \tag{2-20}$$

The σ^2 is a positive number, while ρ lies between –1 and 1. AR(1) covariance structure is often used to fit models where observations have equally spaced longitudinal observations on the same unit of analysis. The structure implies that observations closer to each other in time have higher correlation than observations further apart in time. A more complicated version is unstructured correlation matrix (UNR), which allows that each variance and covariance terms are different.

There are two commonly used methods for estimating fixed and random effects in multilevel regression. These are maximum likelihood method (ML) and restricted maximum likelihood method (REML). Both procedures try to estimate the vectors $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ in such a way that the likelihood function is maximized, meaning that the values of the parameters are set to make the observed values of the dependent variable most likely, given the distribution assumptions (West et al., 2015). However, ML estimates of the covariance parameters are biased, whereas REML estimates are not. On the other hand, ML estimates have an important advantage when testing a hypothesis, as will be explained shortly. The multilevel regression, used in this study, is performed by SPSS Mixed Linear Models function, which allows estimating the model by both procedures, using Newton-Raphson and Fisher scoring computational algorithms (West et al., 2015).

Multilevel regression requires testing hypothesis in a similar way as any regression analysis. Testing individual parameters can be done in two (equivalent) ways. The first way is specifying the hypothesis whether parameter in question has statistically significant impact on the dependent variable and testing it with the appropriate *t*-test, while the second way is comparing the fit of two nested models. A more general model encompasses both the null and the alternative hypothesis, and is called a reference model. A second, simpler model, satisfies the null hypothesis, and is called a nested (null hypothesis) model. These two models are then compared with Likelihood Ratio Test (LRT). The test is based on comparing the values of likelihood function of nested and reference model, which differ in the hypothesis being tested. LRT test can be used for both testing fixed effects and covariance parameters (random effects). Both models, however, need to be fitted on the same subset of data, otherwise log-likelihood values are not comparable. The testing statistics is then defined as shown in *Equation 2-21.*

$$-2log\left(\frac{L_{nested}}{L_{reference}}\right) = -2\log(L_{nested}) - \left(-2\log(L_{reference})\right) \sim \chi^2_{df} \tag{2-21}$$

Likelihood theory states that LRT statistics follows asymptotical χ^2-distribution. Degrees of freedom are obtained by subtracting the number of parameters of the reference model from the number of parameters of the nested model (West et al., 2015). However, testing fixed effects by LRT is allowed only with ML estimates of –2 log-likelihood function, which are comparable among nested models with different number of fixed effect parameters (Field, 2013; Morrell, 1998; Pinheiro & Bates, 1996; Verbeke & Molenberghs, 2000). The model *A* is said to be nested in model *B* if model *A* is a special case of model *B*, meaning that the parameter space for the nested model *A* is a subspace of that for the more general model *B*. The model with the lowest –2 log-likelihood value is assumed to fit the data best. On the other hand, some authors suggest (e.g. Morrell, 1998; West et al., 2015) that for testing covariance parameters (random effects) with LRT method, REML estimations of –2 log-likelihood function should be used. REML reduces the bias inherent in ML estimates of covariance parameters. In case when models are not nested, but still fitted to the same set of the data, Akaike information criteria (AIC) or Bayes information criteria (BIC) should be used.

As a general rule, a lower value of either statistics indicates a better fit (West et al., 2015).

Any statistical software for fitting multilevel models (e.g. SPSS, SAS, R, Stata, HLM, MLwiN) automatically provides *t*-tests for estimated fixed effects. The hypotheses and calculation of *t*-test are shown in *Equation 2-22.*

$$\mathrm{H_0}: \beta_j = 0 \qquad \mathrm{H_1}: \beta_j \neq 0$$
$$t = \frac{\hat{\beta}_j - 0}{se(\hat{\beta}_j)} \tag{2-22}$$

However, there are different methods for determining the appropriate number of degrees of freedom. SPSS uses the Satterthwaite approximation, which takes into account the presence of random effects and correlated residuals in multilevel model (West et al., 2015). Alternatively, Type I and Type III *F*-tests are usually estimated. The latter one, which is more often used, is conditional on the effects of a particular covariate in all other terms in a given model, so it is useful when cross-effects are tested.

Similarly as for fixed effects, two options for testing covariance parameters are available. The first option is Wald *z*-test, which is already given by SPSS. However, researchers (e.g. West et al., 2015; Verbeke & Molenberghs, 2000) strongly suggest using the LRT method. Determining the correct *p*-value is done through χ^2- or a mixture of χ^2-distributions. The first option is used when covariance parameter, satisfying the null hypothesis, does not lie on the boundary of the parameter space (e.g. testing whether a covariance between two random effects is equal to zero). In such cases, testing statistics is asymptotically distributed as a χ^2-distribution, with degrees of freedom calculated by subtracting the number of covariance parameters of the nested model from that of the reference model. The second option is used when the covariance parameter, satisfying the null hypothesis, lies on the boundary of the parameter space (e.g. testing whether a given random effect should be kept in a model or not). For example, in a case of testing variance term of a random effect, the *p*-value is calculated as a mixture of χ_0^2 and χ_1^2, each having 0.5 weight. Furthermore, in a case when there is a variance and one covariance term related to a particular random effect, which is being tested, the *p*-value is calculated as a mixture of χ_1^2 and χ_2^2, each having 0.5 weight, etc. (Verbeke & Molenberghs, 2000).

3 THE APPLICATION OF MULTILEVEL REGRESSION TO THE CASE OF CORPORATE CAPITAL STRUCTURE

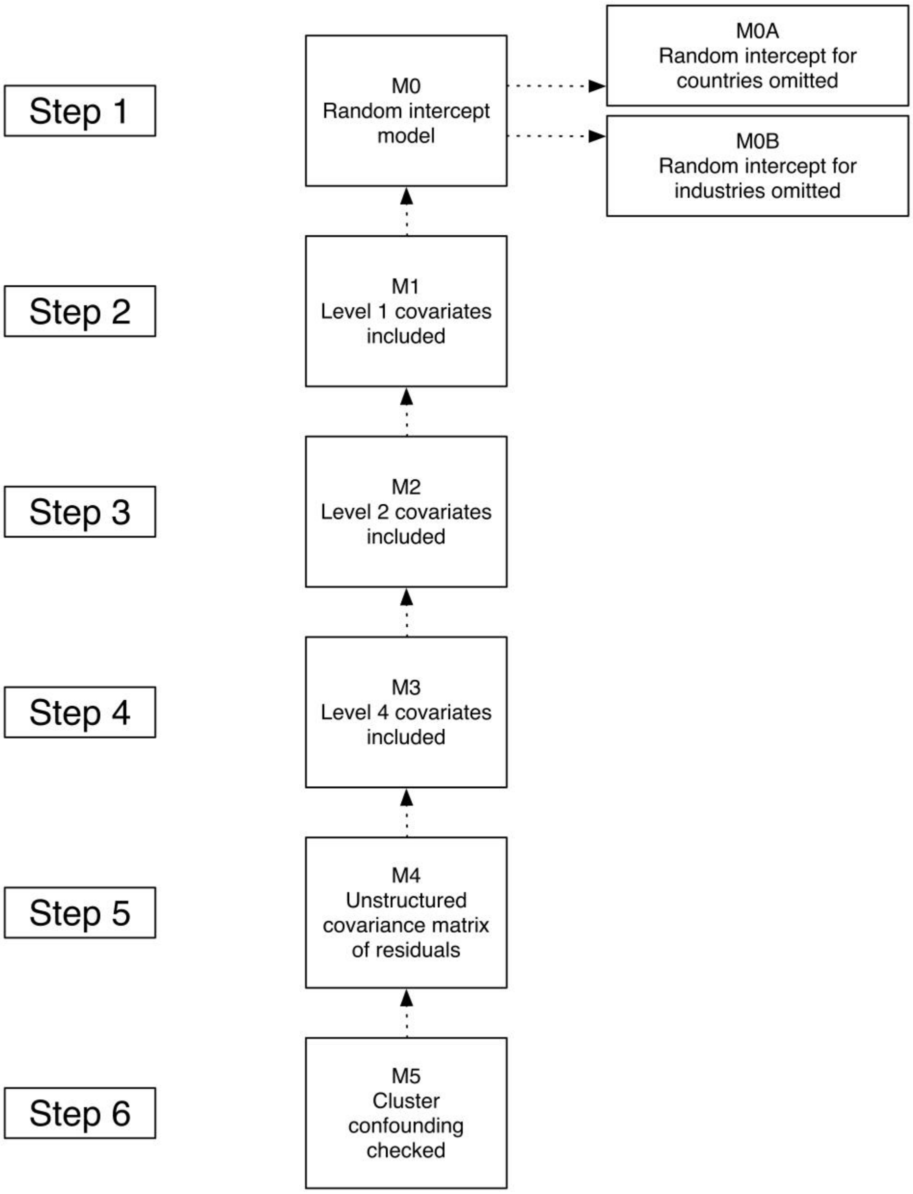
In the third chapter I empirically apply multilevel regression to the financial study of corporate capital structure of European firms – I examine how various predictors can explain corporate capital structure, emphasizing the importance of cluster confounding. Findings are vividly compared with results of other regression techniques. Finally, I use the estimates of the target capital structure to explain why firms try to adjust their capital structures toward their targets.

3.1 Applying multilevel regression to the case of corporate capital structure

In this subchapter I develop the multilevel model for explaining capital structure heterogeneity. As seen in *Figure 3-1*, the model is developed in six steps. The first step is fitting a random intercept model (M0), and then gradually adding level 1 through level 4 explanatory variables. Then, instead of AR(1), unstructured correlation matrix for residuals is used instead. Finally, cluster confounding is addressed. Multilevel linear models are more precisely compared in *Table 3-1*. Since I did not find any theoretical justifications that predictors would have in different industries or countries different impact on leverage ratios, my model omits random slopes.[14]

[14] One could argue that capital structure determinants could have different effects in more or less developed European countries. However, Booth, Aivazian, Demirguc-Kunt, and Maksimovic (2001) clearly showed that there are no systematic differences in the model for estimating the target capital structure between developed and developing countries.

Figure 3-1. *Steps in multilevel regression*



Source: *Own presentation*.

Table 3-1. *Comparison of fitted multilevel models*

		Term/Variable	Notation	Model 0	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed effects		Intercept	β_0	√	√	√	√	√	√
	Level 1	PROFITABILITY	β_1		√	√	√	√	
		SIZE	β_2		√	√	√	√	
		GROWTH	β_3		√	√	√	√	
		TANGIBILITY	β_4		√	√	√	√	
	Level 2	FIN. DISTRESS	β_5			√	√	√	√
		D_{PUBLIC}	β_6			√	√	√	√
		$D_{UNIQUE\ PRODUCTS}$	β_7			√	√	√	√
	Level 4	GDP GROWTH	β_8				√	√	√
		INFLATION	β_9				√	√	√
		TAX RATE	β_{10}				√	√	√
Random effects	Industry (j)	Intercept	$r_{0\ j\|k}$	√	√	√	√	√	√
	Country (k)	Intercept	$u_{0\ k}$	√	√	√	√	√	√
Residuals	Firm-year observation (t)		ε_{tijk}	√	√	√	√	√	√
Covariance parameters $\boldsymbol{\theta_D}$ for D matrix	Industry level (L3)	Variance of intercepts	$\sigma^2_{int:\,Industry}$	√	√	√	√	√	√
	Country level (L4)	Variance of intercepts	$\sigma^2_{int:\,Country}$	√	√	√	√	√	√
Covariance parameters $\boldsymbol{\theta_R}$ for R matrix	Firm-year level (L1)	Residual variance (AR1)	$\sigma^2,\ \rho$	√	√	√	√		
		Residual variance (UNR)	$\sigma^2_t,\ cov_{t_a,t_b}$					√	√
Cluster confounding	Level 1	PROFITABILITY SIZE GROWTH TANGIBILITY	$\beta_1^w\ \ \beta_1^b$ $\beta_2^w\ \ \beta_2^b$ $\beta_3^w\ \ \beta_3^b$ $\beta_4^w\ \ \beta_4^b$						√

Source: *Own presentation.*

3.2 Data and sampling

The empirical analysis utilizes the Amadeus database, provided by Bureau van Dijk (2013). The database contains comprehensive financial information of firms from 34 European countries. Using one single provider ensures consistency and comparability in the treatment of accounting categories. The sample includes firms from 25 countries: Belgium, Bulgaria, Croatia, Czech

Republic, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom (See *Figure 3-2*).

Figure 3-2. *Graphical presentation of included countries*

Source: *Own presentation*.

There are two main reasons why firms from some European countries are excluded from the analysis. First, some countries do not provide firms' financial information back to the year 2005 (e.g. Balkan), and second, some countries do not report all financial categories which are crucial for this study (e.g. for Austrian firms the amount of financial debt was not available). The chosen sample period is 2005–2011. In 2004, some significant changes in accounting were introduced, making the analysis incomparable for prior years. Moreover, for many firms no data are available before the year 2005. Every firm is individually tested for consistency of financial statements with a series of logical tests. Although very few in numbers, observations which fail to satisfy these tests, are removed. Original dataset included a large number of very small private lifestyle firms with diverse and different financing behavior than larger firms. To mitigate this problem, I require that all included firms have sample average total assets exceeding €5 million. Following convention firms operating in regulated industries, i.e. gas, water and electric utilities (NACE Rev. 2: Division 35), are excluded from the analysis (e.g. Byoun, 2008; Lemmon et al., 2008). I also exclude financial firms (e.g. banks, insurance companies, pension funds). Such firms can have very different capital structures and their financing decisions may not show the same information as for non-regulated firms. For example, high leverage can be normal for financial and regulated firms, while the same leverage may indicate possible financial distress for other firms, as discussed by Byoun (2008).

The final sample has 8,777 firms, operating in 25 European countries. The largest subsamples come from the United Kingdom and Germany, while the smallest subsamples from Iceland and Estonia. It needs to be stressed that there is a possible survivorship bias because only firms with complete and consistent financial data during the analyzed time period are included. However, I believe that this does not affect the main findings of this analysis, because as recently shown in a similar study by Lemmon et al. (2008), firms' capital structure behavior does not statistically differ between the general population and the population of survivors. *Table 3-2* shows the frequency distribution of firms by country.

Table 3-2. *Frequency distribution of firms by country*

	Country	Number of firms	Share in %		Country	Number of firms	Share in %
1.	Belgium	736	8.4	14.	Latvia	234	2.7
2.	Bulgaria	178	2.0	15.	Lithuania	252	2.9
3.	Croatia	92	1.0	16.	Luxembourg	99	1.1
4.	Czech Rep.	229	2.6	17.	Norway	81	0.9
5.	Estonia	51	0.6	18.	Poland	476	5.4
6.	Finland	109	1.2	19.	Portugal	150	1.7
7.	France	244	2.8	20.	Slovakia	135	1.5
8.	Germany	1,392	15.9	21.	Slovenia	141	1.6
9.	Greece	334	3.8	22.	Spain	930	10.6
10.	Hungary	184	2.1	23.	Sweden	110	1.3
11.	Iceland	19	0.2	24.	Switzerland	387	4.4
12.	Ireland	187	2.1	25.	UK	1,691	19.3
13.	Italy	336	3.8		Σ	8,777	100.0

Source: Bureau van Dijk, *Amadeus database*, 2013.

Table 3-3 shows the distribution of firms by their primary activity (NACE classification). Most firms come from section C – "Manufacturing", and section G – "Wholesale and retail trade; repair of motor vehicles and motorcycles". On the other hand, the fewest firms operate in section O – "Public administration and defense; compulsory social security", and section P – "Education".

Table 3-3. *Frequency distribution of firms by industry*

Section	**NACE Description**	**Number of firms**	**Share in %**
A	Agriculture, forestry and fishing	127	1.4
B	Mining and quarrying	57	0.6
C	Manufacturing	2,340	26.7
E	Water supply; sewerage, waste management and remediation activities	210	2.4
F	Construction	714	8.1
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	2,273	25.9
H	Transportation and storage	534	6.1
I	Accommodation and food service activities	215	2.4
J	Information and communication	250	2.8
K	Financial and insurance activities	258	2.9
L	Real estate activities	535	6.1
M	Professional, scientific and technical activities	621	7.1
N	Administrative and support service activities	326	3.7
O	Public administration and defense; compulsory social security	14	0.2
P	Education	15	0.2
Q	Human health and social work activities	149	1.7
R	Arts, entertainment and recreation	66	0.8
S	Other service activities	73	0.8
	Σ	8,777	100.0

Source: Bureau van Dijk, *Amadeus database*, 2013.

In *Figure 3-3*, structure and time-series movement of selected balance sheet categories are shown with a boxplot graph[15]. The first five columns show the structure of firms' assets. During the analyzed period, median share of fixed assets in total assets (the 1st column) and median share of current assets in total assets (the 3rd column) represent around 45 and 65 percent, respectively. Both categories are stable.

Fixed assets are mainly composed of tangible assets (the 2nd column) with slightly increasing dispersion from the year 2005 to the year 2011. Stocks as a share of current assets (the 4th column) and debtors as a share of current assets (the 5th column) show no significant movements during the analyzed period. The median share of equity capital in total assets (the 6th column) increased from 28 percent in the period 2005–2008 to 32 percent in the year 2011. On the other hand, the median share of long-term debt in total assets (the 7th column)

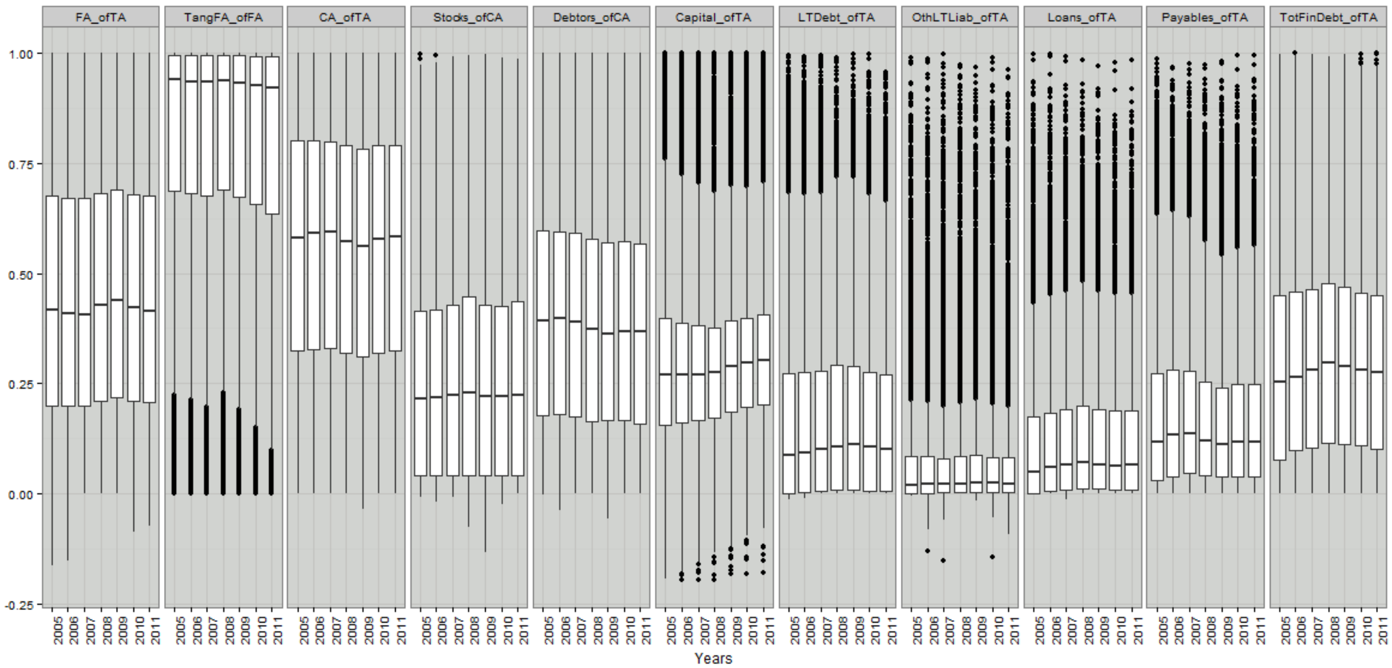
[15] Boxplot represents several values: the minimum, the first quartile, the median, the third quartile, and the maximum, while black points denote outliers. It gives a good impression of where the data is centered and how is dispersed.

increased from the year 2005 to the year 2009 and then fall. Median share of other long-term liabilities in total assets (the 8th column) was stable. Median share of short-term debt in total assets (the 9th column) shows similar pattern as long-term debt. However, the fall is seen already in the year 2009. Median share of accounts payable in total assets shows an increase in the period 2005–2007, then a slight fall in 2008 and 2009, and afterwards it stabilizes. The last column, median share of total financial debt in total assets reveals a strong leveraging process in the period 2005–2008. In the year 2005 this share was 25 percent, while in the year 2008 it reached a peak at 30 percent. After the year 2008, deleveraging process can be observed.

Table 3-4 shows the descriptive statistics for each variable used in the multilevel model. These values relate to the sample of 8,777 firms, however, not all firms have full six year observations, because some firm-year observations are detected by different diagnostic tools and removed from the analysis. Furthermore, to mitigate the effect of outliers and fundamental errors in the data, all continuous variables are winsorized at the upper and lower one-percentile, following similar recent empirical studies. Winsorizing is the transformation of variables by limiting extreme values to reduce the effect of possible spurious outliers. This is usually done in a way that the top and bottom percentiles of an individual variable are transformed into the same value. For example, any value above the 99th percentile of the chosen variable is replaced by the 99th percentile and any value below the 1st percentile is replaced by the value of the 1st percentile. This procedure has an advantage over trimming because observations with extreme values are not removed and thus not lost (Ghosh & Vogt, 2012). This is in line with recently published articles (e.g. Flannery & Rangan, 2006).

Figure 3-3. *Structure of selected balance sheet categories during the period 2005–2011*

Sample size is 8,777 firms. Structure and time-series movement of selected balance sheet categories are shown with boxplots (minimum, first quartile, median, third quartile, and maximum; black points represent outliers). Columns from left to right: **FA_ofTA**: Fixed assets as a share of total assets; **TangFA_ofFA**: Tangible fixed assets as a share of fixed assets; **CA_ofTA**: Current assets as a share of total assets; **Stocks_ofCA**: Stocks as a share of current assets; **Debtors_ofCA**: Debtors as a share of current assets; **Capital_ofTA**: Equity capital as a share of total assets; **LTDebt_ofTA**: Long-term debt as a share of total assets; **OthLTLiab_ofTA**: Other long-term liabilities as a share of total assets; **Loans_ofTA**: Short-term debt as a share of total assets; **Payables_ofTA**: Acc. payable as a share of total assets; **TotFinDebt_ofTA**: Total financial debt as a share of total assets. R-code can be found in Appendix A-1.



Source: Bureau van Dijk, *Amadeus database*, 2013.

Table 3-4. *Descriptive statistics of variables used in the model*

Descriptive statistics relate to the sample of 8,777 firms with average total assets exceeding €5 million, excluding firm-year observations that are removed by diagnostic check. Variables, denoted with an asterisk (*) are winsorized so that values below 1st percentile (above 99th percentile) are replaced with value of 1st percentile (99th percentile). The descriptive statistics for the dependent variable relate to the period 2006–2011 and for the 10 explanatory variables to the period 2005–2010.

Variable	Mean	Standard deviation	1st percentile	Q1	Median	Q3	99th percentile
Dependent variable							
Leverage (% of TA)	30.27	22.30	* 0.00	11.10	28.47	46.33	* 86.18
Level 1							
Profitability (% of TA)	6.12	6.53	* –15.00	2.34	4.96	8.97	* 35.00
Firm size ($\log_{10}$(€))	4.45	0.68	* 3.46	3.93	4.26	4.80	* 6.73
Firm growth (% Δ in TA)	7.41	20.94	* –36.90	–4.11	3.80	15.22	* 94.54
Tangibility (% of TA)	35.54	28.16	* 0.01	11.31	29.16	54.75	* 96.93
Level 2							
Financial distress (% of TA)	3.84	3.05	* 0.22	1.64	3.04	5.16	* 18.63
D_{PUBLIC}	0.36	/	0	0	0	1	1
$D_{UNIQUE\ PRODUCTS}$	0.06	/	0	0	0	0	1
Level 4							
GDP growth (%)	1.53	3.88	–8.50	–0.10	2.30	3.60	10.10
Inflation (%)	2.59	1.93	–1.20	1.80	2.30	3.30	11.10
Tax rate (%)	25.50	6.47	10.00	22.00	25.00	32.00	33.99

Sources: Bureau van Dijk, *Amadeus database*, 2013; Eurostat, 2016.

The dependent variable, *leverage*, is winsorized at 0.00 and 86.18 percent. The average and median values are 30.27 and 28.47 percent, respectively. The first explanatory variable, *profitability*, is distributed between –15.00 and 35.00 percent. The average and median values are 6.12 and 4.96 percent, respectively. The second explanatory variable, *firm size*, is expressed in logarithms of total assets, and has values between 3.46 and 6.73. The average and median values are 4.45 and 4.26, respectively. The third explanatory variable, *firm growth*, has values between –36.90 and 94.54 percent. The average and median values are 7.41 and 3.80 percent, respectively. The fourth explanatory variable, *tangibility*, is distributed between 0.01 and 96.93 percent. The average and median values are 35.54 and 29.16 percent, respectively. All first level explanatory variables are winsorized at 1st and 99th percentile. The fifth explanatory variable, *financial distress*, is dispersed between 0.22 and 18.63 percent and is winsorized. The average and median values are 3.84 and 3.04 percent, respectively. A dummy variable for public firms, D_{PUBLIC}, reveals that 36 percent of all observations belong to public firms. Dummy for firms with unique products, $D_{UNIQUE\ PRODUCTS}$, reveals that 6 percent of all observations belong to firms that are producing unique durable products. The last three variables belong to the fourth level and are not winsorized. During the analyzed period, GDP growth was dispersed between –8.50 and 10.10 percent, with average and median values 1.53 and 2.30 percent, respectively. Inflation was distributed between –1.20 and 11.10 percent. The average and median values are 2.59 and 2.30 percent, respectively. Corporate tax rate was distributed between 10.00 and 33.99 percent, with average and median values 25.50 and 25.00 percent, respectively.

Checking the model assumptions. Before building the multilevel model, data needs to be statistically checked for consistency. The analysis usually starts with estimating the preliminary model, and then analyzing residuals and performing influential diagnostic, which is the common name for techniques that allow to identify observations that heavily influence estimates of the parameters in either $\boldsymbol{\beta}$ or $\boldsymbol{\theta}$. However, because the majority of programs for multilevel modeling (including SPSS) does not currently offer procedures to perform influential diagnostic, the full model is usually first estimated as a multiple regression model and in addition to analyzing residuals, influential diagnostic is performed. I assume that the same observations that would importantly influence the results obtained with multiple regression analysis would also negatively impact the results obtained with multilevel regression. Analysis of residuals and all influential diagnostics together, presented in this subchapter, decreased the sample size from 8,996 firms to 8,777 firms.[16] As a robustness check, multilevel regression is also performed on the full sample of 8,996 firms and none of the

[16] After the influential diagnostics, 7,670 firms have full six year observations, 594 firms have five year observations, 239 firms have four year observations, 136 firms have three year observations, 92 firms have two year observations, and 46 firms have one year observation.

estimated regression coefficients significantly changed; however, the model fit was worse.

Outliers and residuals. An outlier is a case that differs substantially from the main trend of the data (Field, 2013). The difference between the observed outcome and the outcome, predicted by the model, is known as a residual. There are three types of residuals used to analyze the model assumptions. The first are normal or unstandardized residuals, but they are hard to compare among units. This can be solved by analyzing standardized residuals, most often converting them into z-scores. There is also another option, called studentized residuals, which are the unstandardized residuals, divided by an estimate of their standard deviation that varies point by point (Field, 2013). These residuals have the same properties as the usual standardized residuals, but provide a more precise estimate of the error variance of a specific case.

Influential diagnostics. There are six influential diagnostics, which are often used in the regression analysis. (1) Cook's distance. It measures the aggregate impact of each observation on the group of regression coefficients, as well as on the group of fitted values. It is thus a measure of the change in the regression coefficients that would occur if this case was omitted, revealing which cases are most influential in affecting the regression equation (Stevens, 2009). Values, larger than $4/n$, where n is the number of observations, are considered highly influential (Chen et al., 2003). (2) Mahalanobis distance. It measures the distance of cases from the means of the explanatory variables. Mahalanobis distance is distributed by χ^2-distribution with degrees of freedom equal to the number of explanatory variables. Units, for which Mahalanobis distance exceeds the critical χ^2-value, are considered to be outliers. The usual level of significance is set to 0.001 (Tabachnick & Fidell, 2012). (3) Centered leverage value (Hat Diag). It measures how far an observation is from others in terms of the levels of the independent variables. There are different suggestions for a cut-off point, however, $(2(k+1))/n$, $(2(k+2))/n$, or $(3(k+1))/n$ are used most often, k being the number of predictors and n being the sample size (Field, 2013; Chen et al., 2003). (4) Standardized DFBETAs. They measure how much an observation affects the estimates of regression coefficients – there are that many DFBETAs as there are regression coefficients, including the intercept. When using the standardized DFBETAs, cases with absolute values above

$2/\sqrt{n}$, where n is number of observations, have substantial influence (Field, 2013; Chen et al., 2003). (5) Standardized DFFITS. This statistic indicates how much predicted value of an observation will change if this observation is removed from the analysis (Stevens, 2009). It is thus a difference between the predicted value for a case when a model is estimated including that case, and when the model is estimated excluding this case. Standardized values in absolute terms, larger than $2\sqrt{(k+1)/n}$, where k is the number of predictors and n is sample size, are considered highly influential (Field, 2013; Chen et al., 2003). (6) Covariance ratio. It measures whether a case influences the variance of the regression parameters. Values outside the interval $1\pm3(k+1)/n$, where k is the number of predictors and n is sample size, are considered highly influential (Field, 2013).

Multicolinearity. Many statisticians stress the importance of centering a variable around its grand mean (e.g. Snijders & Boske, 2012). There are two main benefits of doing this. First, it facilitates the explanation of the model in a way that it gives the meaning to the regression intercept. Second, the more important reason is that centering reduces the problem of multicolinearity among explanatory variables, which can have quite a negative impact on the estimation of multilevel model (Tabachnick & Fidell, 2012). Multicolinearity is defined as a strong correlation between two or more explanatory variables in a regression model. One possible way to identify multicolinearity is to scan correlation matrix of explanatory variables to see if any correlate highly (usually above $|0.8|$). The other option is to check variance inflation factor (VIF), where values above 10 are considered high. Equivalently, tolerance statistic for variables with value below 0.10 is considered problematic (Field, 2013).

Estimation of multiple regression model for initial diagnostic check. The model with 10 explanatory variables was fitted as a multiple regression function. For each observation (53,976 firm-year observations), all of the previously described diagnostics were checked. These are studentized residuals, Cook’s distance, Mahalanobis distance, centered leverage value, standardized DFBETAs, standardized DFFITS, and covariance ratio. Additionally, multicolinearity check was done for the explanatory variables. As explained, only firms with all available values of explanatory variables for the entire analyzed period were used so there was no problem with missing data. *Table 3-5* shows the cutting values for each of diagnostics used.

Table 3-5. *Diagnostic check*

Check	Statistic used	Removed observations/variables
Outliers	Studentized residuals (SR)	$\lvert SR \rvert \geq 3.29$
Influential diagnostic	Cook's distance (CD)	$CD \geq 0.00007$
	Mahalanobis distance (MD)	$MD \geq 29.59$
	Centered leverage value (LV)	$LV \geq 0.0004$
	Standardized DFBET (DFB)	$\lvert DFB \rvert \geq 0.0086$
	Standardized DFFITS (DFF)	$\lvert DFF \rvert \geq 0.0286$
	Covariance ratio (CR)	$0.9994 \leq CR \; or \; CR \geq 1.00061$
Multicolinearity	VIF	$VIF \geq 10$
	Tolerance (T)	$T \leq 0.10$

Source: Bureau van Dijk, *Amadeus database*, 2013.

I remove all firm-year observations that do not fulfill requirements described in *Table 3-5*. This procedure decreases sample size from 53,976 firm-year observations to 50,584 firm-year observations. However, one of the important advantages of multilevel regression is that the method does not require that firms have the same number of repeated observations, as argued by many authors (e.g. Gelman & Hill, 2007; Field, 2013; Tabachnik & Fidell, 2012). In some other multivariate methods (e.g. ANOVA or ANCOVA), such units would simply be removed from the analysis. I also check multicolinearity among 10 explanatory variables. Explanatory variable *Tax rate* has the highest VIF, which is equal to 1.254 (tolerance 0.797). Since this value is far below the critical boundary, I assume that there is no problem with multicolinearity. Consequently, I do not center the data, which is one of the options for decreasing correlation among explanatory variables. The result of multiple regression, which is already fitted on 50,584 observations, is shown in *Appendix B-0*. However, this model is neither controlled for cross-sectional dependency neither for time-series dependency. The results are therefore not reliable, but are compared to findings of multilevel regression. In *Appendix B-0*, a histogram of residuals and P-P plot for normality are presented. Both show that residuals are approximately normally distributed. Moreover, I estimate the multiple regression model, which is controlled for time-series dependency, and is also compared with the final results (see *Appendix B-1*).

3.3 Variation of leverage

Researchers found that there are large cross-sectional differences in indebtedness among firms (Kayhan & Titman, 2007; Lemmon et al., 2008; Strebulaev & Yang, 2013). To verify their findings, I further decompose the variability of $Leverage_{tijk}$, defined either as long-term debt or total financial debt relative to total assets, into four parts: (a) within-firm variability, (b) between-firm variability, (c) between-industry variability, and (d) between-country variability. Lemmon and Zender (2010) found that during their 20-year period, approximately 60 percent of leverage variation is cross-sectional, which means that leverage varies more cross-sectionally than within-firm. Graham and Leary (2011) performed a similar analysis over even longer time period and found that 42 percent of variation is within-firm, 44 percent within-industry and 14 percent between-industry. The majority of cross-sectional variation is thus contributed by firms operating within the same industry, which was also confirmed by MacKay and Phillips (2005). They found that within-industry variation of book leverage is three times larger than between-industry variation. Decomposition is shown below.

$$\begin{aligned}
\sum_t \sum_i \sum_j \sum_k \left(L_{tijk} - \bar{L}_{....}\right)^2 \\
&= \sum_t \sum_i \sum_j \sum_k \left[\left(L_{tijk} - \bar{L}_{.ijk}\right) + \left(\bar{L}_{.ijk} - \bar{L}_{..jk}\right)\right. \\
&\quad \left. + \left(\bar{L}_{..jk} - \bar{L}_{...k}\right) + \left(\bar{L}_{...k} - \bar{L}_{....}\right)\right]^2 \\
&= \sum_t \sum_i \sum_j \sum_k \left(L_{tijk} - \bar{L}_{.ijk}\right)^2 \\
&\quad + \sum_t \sum_i \sum_j \sum_k \left(\bar{L}_{.ijk} - \bar{L}_{..jk}\right)^2 \\
&\quad + \sum_t \sum_i \sum_j \sum_k \left(\bar{L}_{..jk} - \bar{L}_{...k}\right)^2 \\
&\quad + \sum_t \sum_i \sum_j \sum_k \left(\bar{L}_{...k} - \bar{L}_{....}\right)^2
\end{aligned}$$

In this specification, L_{tijk} is leverage in year *t* for firm *i*, operating within industry *j* and country *k*; $\bar{L}_{.ijk}$ is average leverage for firm *i* operating within industry *j* and country *k*; $\bar{L}_{..jk}$ is average leverage for industry *j* within country *k*;

$\bar{L}_{...k}$ is average leverage for country k; and $\bar{L}_{....}$ is a grand mean – average leverage of all firm-year observations. The results are shown in *Table 3-6*.

Table 3-6. *Decomposition of leverage variability*

	% of total variation of leverage	
	Long-term debt	Total financial debt
Within firm	14.8	15.2
Between firms within the same industry	51.8	59.6
Between industries within the same country	24.2	15.4
Between countries	9.2	9.8

Note: Sample size is 8,777 firms. Time period is 2006–2011.

Source: Bureau van Dijk, *Amadeus database*, 2013.

Table 3-6 reveals that during six-year period, between-firm heterogeneity of leverage is much larger compared to within-firm heterogeneity. Comparing within-firm heterogeneity of long-term debt and total financial debt, there is little difference. This means that firms are rarely taking and returning new short-term credit, which would result in an increased heterogeneity of total financial debt. The between-firm heterogeneity shows an important increase when leverage is defined as total financial debt. This means that there is a significant share of firms that are financed primarily with short-term debt, which causes increased heterogeneity. In contrast, between-industry heterogeneity is significantly decreased when total financial debt is analyzed. This means that access to long-term debt is highly influenced by the industry in which the firm operates. The distinction between the ability to borrow long- or short-term was highlighted by Diamond (1991). Finally, between-country heterogeneity is the smallest, meaning that countries are relatively homogenous regarding corporate indebtedness, defined either as long-term debt or total financial debt. However, the decomposition shows that there are significant differences in leverage both between industries and countries. That means that the random intercept model, which allows the intercept to vary freely among the higher-level groups, should be used.

3.4 Comparison of regression models results

3.4.1 Model 0

The first fitted model, Model 0, is the model without any explanatory variables, controlled only for the hierarchical structure of data – random intercept model. Model includes the random intercept for industries and countries.[17] It is written in *Equation 3-1*.

$$\begin{aligned} &Leverage_{tijk} = \beta_0 + u_{0\,k} + r_{0\,j|k} + \varepsilon_{tijk} \\ &u_{0\,k} \sim N\left(0, \sigma^2_{int:\,Country}\right) \quad r_{0\,j|k} \sim N\left(0, \sigma^2_{int:\,Industry}\right) \quad \varepsilon_{tijk} \sim N\left(0, \sigma^2\right) \end{aligned} \tag{3-1}$$

In this specification, $Leverage_{tijk}$ represents the value of the dependent variable in time *t* for firm *i*, operating within industry *j* and country *k*. β_0 is a fixed intercept. $u_{0\,k}$ is the random effect associated with the intercept for country *k*, $r_{0\,j|k}$ is the random effect associated with the intercept for industry *j* within country *k*, and ε_{tijk} is the residual. The distribution of random effects is assumed to follow normal distribution. $\sigma^2_{int:\,Country}$ represents the variance of the country-specific random intercept, and $\sigma^2_{int:\,Industry}$ represents the variance of the random industry-specific intercepts at any given country. Finally, σ^2 represents the residual variance. The full SPSS output of this model is presented in Appendix B-3, with the main findings highlighted in *Equation 3-2*.

$$\begin{aligned} &\widehat{Leverage}_{tijk} = 27.332 \\ &u_{0\,k} \sim N\left(0, 65.71\right) \quad r_{0\,j|k} \sim N\left(0, 95.04\right) \quad \varepsilon_{tijk} \sim N\left(0, 384.00\right) \end{aligned} \tag{3-2}$$

Test of random intercept on the country level was performed indirectly through testing its variance: comparing –2 REML log-likelihood of a nested model $(\mathrm{H_0} - \mathrm{Model\,0A})$ with a reference model $(\mathrm{H_1} - \mathrm{Model\,0})$. Test statistic is distributed asymptotically as $0.5 \cdot \chi^2_{df=0} + 0.5 \cdot \chi^2_{df=1}$.

$$H_0\colon \sigma^2_{int:\,Country} = 0 \; (drop\; u_{0\,k}) \qquad H_1\colon \sigma^2_{int:\,Country} > 0 \; (retain\; u_{0\,k})$$

–2 REML log-likelihood of a nested model (M0A): 378210.3
–2 REML log-likelihood of a reference model (M0): 378141.6

[17] I would like to stress that estimating the model with inclusion of random intercept for firms (Level 2) is infeasible due to a very large number of firms and the model does not converge.

$$\chi^2_{df=0:1} = \Delta - 2\ REML\ LL = (-2\ LL_{M0A}) - (-2\ LL_{M0}) = 378210.3 - 378141.6 = 68.7$$

$$p-value = 0.5 \cdot P(\chi^2_{df=0} > 68.7) + 0.5 \cdot P(\chi^2_{df=1} > 68.7) < 0.001$$

Based on χ^2-test I conclude that the variance of intercepts among countries is positive, and retain the random effect associated with intercept on country level in this and all subsequent models (M0 is preferred over model M0A).

$$H_0: \sigma^2_{int:\,Industry} = 0\ (drop\ r_{0\ j|k}) \qquad H_1: \sigma^2_{int:\,Industry} > 0\ (retain\ r_{0\ j|k})$$

Test of random intercept on the industry level is performed indirectly through testing its variance: comparing –2 REML log-likelihood of a nested model $(\mathrm{H_0} - \text{Model 0B})$ with a reference model $(\mathrm{H_1} - \text{Model 0})$. Test statistic is distributed asymptotically as $0.5 \cdot \chi^2_{df=0} + 0.5 \cdot \chi^2_{df=1}$.

–2 REML log-likelihood of a nested model (M0B): 379475.6
–2 REML log-likelihood of a reference model (M0): 378141.6

$$\chi^2_{df=0:1} = \Delta - 2\ REML\ LL = (-2\ LL_{M0B}) - (-2\ LL_{M0}) = 379475.6 - 378141.6 = 1334$$

$$p-value = 0.5 \cdot P(\chi^2_{df=0} > 1334) + 0.5 \cdot P(\chi^2_{df=1} > 1334) < 0.001$$

Based on χ^2-test I conclude that the variance of intercepts among industries in a given country is positive, and retain the random effect associated with intercept on industry level in this and all subsequent models (M0 is preferred over model M0B).

3.4.1.1 Intraclass correlation

The model without explanatory variables is useful for calculation of intraclass correlation (hereafter ICC), which indicates the proportion of total variance of the dependent variable that is attributed to different levels of the data (Hox, 2010; Tabachnick & Fidell, 2012). With ICC I formally show that there is a strong reasoning to control for a hierarchical structure of the data, i.e. allowing the intercept to freely vary among higher level units. It was shown that even small values of ICCs (around 0.1 and above) can critically inflate Type I error, if the model is not specified in a hierarchical form. In my model I allow the intercept to freely vary between industries (3rd level units) and countries (4th level units) and, hence, I estimate two ICCs, as shown in *Equation 3-3*.

$$ICC_3 = \frac{\sigma_r^2}{\sigma_u^2 + \sigma_r^2 + \sigma^2} \qquad ICC_4 = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_r^2 + \sigma^2} \tag{3-3}$$

ICC can also be interpreted as the expected correlation between two randomly selected units, clustered within the same group. However, in that case Hox (2010) suggested using adjusted equation for lower level ICC, because two randomly selected units in the same lower level group are automatically nested within the same higher level group (*Equation 3-4)*.

$$ICC_3^* = \frac{\sigma_r^2 + \sigma_u^2}{\sigma_u^2 + \sigma_r^2 + \sigma^2} \qquad ICC_4 = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_r^2 + \sigma^2} \tag{3-4}$$

Results of ICCs are shown in *Table 3-7*.

Table 3-7. *Intraclass correlations on industry and country level*

Industry level		Country level
ICC_3	ICC_3^*	ICC_4
0.174	0.295	0.121

Note: All variance terms, used to estimate ICCs, are statistically significant at $p < 0.01$.

Source: Bureau van Dijk, *Amadeus database*, 2013.

Table 3-7 shows that 17.4 percent (29.5 percent) of total variability of leverage is explained by variability between industries (between industries and countries), while 12.1 percent of total variability of leverage is explained by variability between countries. Given that both ICCs exceed 10 percent, controlling for the hierarchical structure of the data is highly advisable. Results clearly show that performing classical OLS regression analysis, without modeling hierarchical structure of the data, would importantly violate the assumption of cross-sectional independence between analyzed firms. Furthermore, AR(1) covariance type shows that autoregression coefficient ρ is 0.894 (see Appendix B-3), which reveals high serial correlation among repeated observations of the same firm. According to Hox (2010), the next step is including fixed effect of the first level predictors.

3.4.2 Model 1

In Model 1, fixed effects on the first level are added. The model is written in *Equation 3-5*.

$$Leverage_{tijk} = \beta_0 + \beta_1 \cdot Profitability_{(t-1)ijk} + \beta_2 \cdot Firm\ size_{(t-1)ijk} + \beta_3 \cdot Firm\ growth_{(t-1)ijk} + \beta_4 \cdot Tangibility_{(t-1)ijk} + u_{0\,k} + r_{0\,j|k} + \varepsilon_{tijk} \quad (3\text{-}5)$$
$$u_{0\,k} \sim N\left(0, \sigma^2_{int:\,Country}\right) \quad r_{0\,j|k} \sim N\left(0, \sigma^2_{int:\,Industry}\right) \quad \varepsilon_{tijk} \sim N\,(0, \sigma^2)$$

In this specification, $Leverage_{tijk}$ represents the value of the dependent variable in time *t* for firm *i*, operating within industry *j* and country *k*. β_0 is a fixed intercept and β_1 till β_4 are fixed effects for the first level explanatory variables. $u_{0\,k}$ is the random effect associated with the intercept for country *k*, $r_{0\,j|k}$ is the random effect associated with the intercept for industry *j*, and ε_{tijk} is the residual. The distribution of random effects is assumed to follow normal distribution. $\sigma^2_{int:\,Country}$ represents the variance of the country-specific random intercept, and $\sigma^2_{int:\,Industry}$ represents the variance of the random industry-specific intercepts at any given country. Finally, σ^2 represents the residual variance. The full SPSS output of this model is presented in Appendix B-4, while the main findings are shown in *Equation 3-6*.

$$\widehat{Leverage}_{tijk} = 3.738 - 0.017 \cdot Profitability_{(t-1)ijk} + 4.291 \cdot Firm\ size_{(t-1)ijk} + 0.028 \cdot Firm\ growth_{(t-1)ijk} + 0.120 \cdot Tangibility_{(t-1)ijk} \quad (3\text{-}6)$$
$$u_{0\,k} \sim N\,(0, 60.26) \quad r_{0\,j|k} \sim N\,(0, 69.81) \quad \varepsilon_{tijk} \sim N\,(0, 365.18)$$

I test whether first level covariates have statistically significant effect on leverage. This can be done with *t*-tests, which are all highly statistically significant for all predictors, except *Profitability* (see Appendix B-4). However, it is suggested to compare –2 log-likelihood of reference model with four fixed effects (Model 1) with nested model (Model 0).

$$H_0: Fixed\ effects\ of\ 1^{st}\ level\ covariates\ are\ zero\ (\beta_1 = \beta_2 = \beta_3 = \beta_4 = 0)$$
$$H_1: At\ least\ one\ of\ fixed\ effects\ at\ the\ 1^{st}\ level\ is\ different\ from\ zero$$

I compare –2 ML log-likelihood of nested model ($\mathrm{H_0} - \mathrm{Model\ 0}$) with reference model ($\mathrm{H_1} - \mathrm{Model\ 1}$). Test statistic is distributed asymptotically by $\chi^2_{df=4}$.

–2 ML log-likelihood of nested model (M0): 378141.6

–2 ML log-likelihood of reference model (M1): 377307.7

$$\chi^2_{df=4} = \Delta - 2\ ML\ LL = (-2\ LL_{M0}) - (-2\ LL_{M1}) = 378141.6 - 377307.7 = 833.9$$
$$\chi^2_{df=4,\ critial,\ \alpha=0.0001} = 23.5$$

Model 1 is preferred over Model 0 at a very high level of significance. Additionally, three *t*-tests of fixed effects of the first level explanatory variables are highly statistically significant, while *p*-value of *Profitability* is 0.055. In Model 2, fixed effects on the second level are added.

3.4.3 Model 2

In Model 2, fixed effects on the first and second level are estimated, as shown in *Equation 3-7*.

$$\begin{aligned} &Leverage_{tijk} = \beta_0 + \beta_1 \cdot Profitability_{(t-1)ijk} + \beta_2 \cdot Firm\ size_{(t-1)ijk} + \\ &\beta_3 \cdot Firm\ growth_{(t-1)ijk} + \beta_4 \cdot Tangibility_{(t-1)ijk} + \beta_5 \cdot \\ &Fin.distress_{ijk} + \beta_6 \cdot Public_{ijk} + \beta_7 \cdot Unique\ products_{ijk} + u_{0\,k} + \\ &r_{0\,j|k} + \varepsilon_{tijk} \\ &u_{0\,k} \sim N\left(0, \sigma^2_{int:\,Country}\right) \quad r_{0\,j|k} \sim N\left(0, \sigma^2_{int:\,Industry}\right) \quad \varepsilon_{tijk} \sim N\left(0, \sigma^2\right) \end{aligned} \tag{3-7}$$

In this specification, $Leverage_{tijk}$ represents the value of the dependent variable in time *t* for firm *i*, operating within industry *j* and country *k*. β_0 is a fixed intercept and β_1 till β_7 are fixed effects for the first and second level explanatory variables. $u_{0\,k}$ is the random effect associated with the intercept for country *k*, $r_{0\,j|k}$ is the random effect associated with the intercept for industry *j*, and ε_{tijk} is the residual. The distribution of random effects is assumed to follow normal distribution. $\sigma^2_{int:\,Country}$ represents the variance of the country-specific random intercept, and $\sigma^2_{int:\,Industry}$ represents the variance of the random industry-specific intercepts at any given country. Finally, σ^2 represents the residual variance. The full SPSS output of this model is presented in Appendix B-5, while the model is written in *Equation 3-8*.

$$\begin{aligned} &\widehat{Leverage}_{tijk} = 7.746 - 0.011 \cdot Profitability_{(t-1)ijk} + 4.265 \cdot \\ &Firm\ size_{(t-1)ijk} + 0.028 \cdot Firm\ growth_{(t-1)ijk} + 0.113 \cdot \\ &Tangibility_{(t-1)ijk} - 0.563 \cdot Fin.distress_{ijk} - 3.117 \cdot Public_{ijk} - \\ &3.068 \cdot Unique\ products_{ijk} \\ &u_{0\,k} \sim N\,(0, 62.85) \quad r_{0\,j|k} \sim N\,(0, 64.63) \quad \varepsilon_{tijk} \sim N\,(0, 361.89) \end{aligned} \tag{3-8}$$

I test whether second level covariates have statistically significant effect on leverage. All *t*-tests are statistically significant. The comparison of –2 log-likelihood of reference model with additional three fixed effects on the second level (Model 2) with the nested model (Model 1) is done below.

$$H_0: Fixed\ effects\ of\ 2^{nd}\ level\ covariates\ are\ zero\ (\beta_5 = \beta_6 = \beta_7 = 0)$$
$$H_1: At\ least\ one\ of\ fixed\ effects\ at\ the\ 2^{nd}\ level\ is\ different\ from\ zero$$

I compare –2 ML log-likelihood of nested model ($\mathrm{H_0}$ − Model 1) with reference model ($\mathrm{H_1}$ − Model 2). Test statistic is distributed asymptotically by $\chi^2_{df=3}$.

–2 ML log-likelihood of nested model (M1): 377307.7
–2 ML log-likelihood of reference model (M2): 377169.5

$$\chi^2_{df=3} = \Delta - 2\ ML\ LL = (-2\ LL_{M1}) - (-2\ LL_{M2}) = 377307.7 - 377169.5 = 138.2$$
$$\chi^2_{df=3,\ critial,\ \alpha=0.0001} = 21.1$$

Model 2 is preferred over Model 1 at a very high level of significance. Additionally, all *t*-tests of fixed effects of the second level explanatory variables are highly statistically significant. In Model 3, fixed effects on the third level are included.

3.4.4 Model 3

In Model 3, fixed effects on the first, second and fourth level are estimated, as shown in *Equation 3-9*.

$$\begin{aligned} &Leverage_{tijk} = \beta_0 + \beta_1 \cdot Profitability_{(t-1)ijk} + \beta_2 \cdot Firm\ size_{(t-1)ijk} + \\ &\beta_3 \cdot Firm\ growth_{(t-1)ijk} + \beta_4 \cdot Tangibility_{(t-1)ijk} + \beta_5 \cdot \\ &Fin.distress_{ijk} + \beta_6 \cdot Public_{ijk} + \beta_7 \cdot Unique\ products_{ijk} + \beta_8 \cdot \\ &GDP_{(t-1)k} + \beta_9 \cdot Inflation_{(t-1)k} + \beta_{10} \cdot Tax\ rate_k + u_{0\,k} + r_{0\,j|k} + \varepsilon_{tijk} \\ &u_{0\,k} \sim N\left(0, \sigma^2_{int:\,Country}\right) \quad r_{0\,j|k} \sim N\left(0, \sigma^2_{int:\,Industry}\right) \quad \varepsilon_{tijk} \sim N\,(0, \sigma^2) \end{aligned} \tag{3-9}$$

In this specification, $Leverage_{tijk}$ represents the value of the dependent variable in time *t* for firm *i*, operating within industry *j* and country *k*. β_0 is a fixed intercept and β_1 till β_{10} are fixed effects for the first, second and fourth level explanatory variables. $u_{0\,k}$ is the random effect associated with the intercept for country *k*, $r_{0\,j|k}$ is the random effect associated with the intercept for industry *j*, and ε_{tijk} is the residual. The distribution of random effects is assumed to follow normal distribution. $\sigma^2_{int:\,Country}$ represents the variance of the country-specific random intercept, and $\sigma^2_{int:\,Industry}$ represents the variance of the random industry-specific intercepts at any given country. Finally, σ^2 represents the residual variance. The full SPSS output of this model is presented in Appendix B-6, while the model is written in *Equation 3-10*.

$$\widehat{Leverage}_{tijk} = 5.456 - 0.016 \cdot Profitability_{(t-1)ijk} + 4.224 \cdot Firm\ size_{(t-1)ijk} + 0.029 \cdot Firm\ growth_{(t-1)ijk} + 0.114 \cdot Tangibility_{(t-1)ijk} - 0.562 \cdot Fin.distress_{ijk} - 3.105 \cdot Public_{ijk} - 3.064 \cdot Unique\ products_{ijk} + 0.035 \cdot GDP_{(t-1)k} + 0.105 \cdot Inflation_{(t-1)k} + 0.092 \cdot Tax\ rate_k \tag{3-10}$$

$$u_{0\,k} \sim N\,(0, 62.19) \quad r_{0\,j|k} \sim N\,(0, 64.45) \quad \varepsilon_{tijk} \sim N\,(0, 361.54)$$

I test whether fourth level covariates have statistically significant effect on leverage; GDP growth and inflation have statistically significant fixed effects, but *t*-test for tax rate is insignificant. However, statistical insignificance is not yet a reason to exclude variable from the model, as argued for example by Tabachnik and FIdell (2012). The comparison of –2 log-likelihood of reference model with fixed effects on the fourth level (Model 3) with the nested model (Model 2) is performed.

$$H_0: Fixed\ effects\ of\ 4^{th}\ level\ covariates\ are\ zero\ (\beta_8 = \beta_9 = \beta_{10} = 0)$$
$$H_1: At\ least\ one\ of\ fixed\ effects\ at\ the\ 4^{th}\ level\ is\ different\ from\ zero$$

I compare –2 ML log-likelihood of nested model (H_0 − Model 2) with reference model (H_1 − Model 3). Test statistic is asymptotically distributed by $\chi^2_{df=3}$.

–2 ML log-likelihood of nested model (M2): 377169.5
–2 ML log-likelihood of reference model (M3): 377114.5

$$\chi^2_{df=3} = \Delta - 2\ ML\ LL = (-2\ LL_{M2}) - (-2\ LL_{M3}) = 377169.5 - 377114.5 = 55.0$$
$$\chi^2_{df=3,\ critial,\ \alpha=0.0001} = 21.1$$

Model 3 is preferred over Model 2 at a very high level of significance. Additionally, two out of three *t*-tests for fixed effects on the fourth level are highly statistically significant. It can be noticed that 10 explanatory variables decreased the variance of random intercepts on the third and fourth level, as was expected. There is also a decrease in residual variance of ε_{tijk}: the difference between Model 0 and Model 3 is 22.46 $(384.0 - 361.54)$, the decrease of 5.8 percent. In the next step, Model 4 is estimated. Instead of AR(1) residual matrix, unstructured residual matrix is used.

3.4.5 Model 4

In Model 4, 10 explanatory variables from Model 3 are used, as shown in *Equation 3-11*. The difference between both models is in the structure of the residual matrix.

$$\begin{aligned}
&Leverage_{tijk} = \\
&\beta_0 + \beta_1 \cdot Profitability_{(t-1)ijk} + \beta_2 \cdot Firm\ size_{(t-1)ijk} + \beta_3 \cdot \\
&Firm\ growth_{(t-1)ijk} + \beta_4 \cdot Tangibility_{(t-1)ijk} + \beta_5 \cdot Fin.distress_{ijk} + \\
&\beta_6 \cdot Public_{ijk} + \beta_7 \cdot Unique\ products_{ijk} + \beta_8 \cdot GDP_{(t-1)k} + \beta_9 \cdot \\
&Inflation_{(t-1)k} + \beta_{10} \cdot Tax\ rate_k + u_{0\,k} + r_{0\,j|k} + \varepsilon_{tijk} \\
&u_{0\,k} \sim N\left(0, \sigma^2_{int:\,Country}\right) \quad r_{0\,j|k} \sim N\left(0, \sigma^2_{int:\,Industry}\right) \quad \varepsilon_{tijk} \sim N\left(0, \sigma^2_t\right)
\end{aligned} \tag{3-11}$$

In this specification, $Leverage_{tijk}$ represents the value of the dependent variable in time *t* for firm *i*, operating within industry *j* and country *k*. β_0 is a fixed intercept and β_1 till β_{10} are fixed effects for the first, second and fourth level explanatory variables. $u_{0\,k}$ is the random effect associated with the intercept for country *k*, $r_{0\,j|k}$ is the random effect associated with the intercept for industry *j*, and ε_{tijk} is the residual. The distribution of random effects is assumed to follow normal distribution. $\sigma^2_{int:\,Country}$ represents the variance of the country-specific random intercept, and $\sigma^2_{int:\,Industry}$ represents the variance of the random industry-specific intercepts at any given country. Finally, σ^2_t represents the residual variance. The full SPSS output of this model is presented in Appendix B-7, while the model is written in *Equation 3-12*.

$$\begin{aligned}
&\widehat{Leverage}_{tijk} = 3.464 - 0.050 \cdot Profitability_{(t-1)ijk} + 4.746 \cdot \\
&Firm\ size_{(t-1)ijk} + 0.030 \cdot Firm\ growth_{(t-1)ijk} + 0.118 \cdot \\
&Tangibility_{(t-1)ijk} - 0.542 \cdot Fin.distress_{ijk} - 3.260 \cdot Public_{ijk} - \\
&3.079 \cdot Unique\ products_{ijk} + 0.020 \cdot GDP_{(t-1)k} + 0.146 \cdot \\
&Inflation_{(t-1)k} + 0.080 \cdot Tax\ rate_k \\
&u_{0\,k} \sim N\,(0, 68.97) \quad r_{0\,j|k} \sim N\,(0, 61.18) \quad \varepsilon_{tijk} \sim N\,(0, \sigma^2_t)
\end{aligned} \tag{3-12}$$

The difference between the nested model (M3) and the reference model (M4) is in the structure of the R-matrix. Model 3 has a restriction that the R-matrix is AR(1) type, while Model 4 has unstructured matrix. All Wald *z*-tests for unstructured matrix are highly statistically significant (see Appendix B-7), however, it is recommended to perform log-likelihood test.

$$
\boldsymbol{H_0}: \boldsymbol{R} = \begin{pmatrix}
\sigma^2 & \sigma^2\rho^1 & \sigma^2\rho^2 & \sigma^2\rho^3 & \sigma^2\rho^4 & \sigma^2\rho^5 \\
\sigma^2\rho^1 & \sigma^2 & \sigma^2\rho^1 & \sigma^2\rho^2 & \sigma^2\rho^3 & \sigma^2\rho^4 \\
\sigma^2\rho^2 & \sigma^2\rho^1 & \sigma^2 & \sigma^2\rho^1 & \sigma^2\rho^2 & \sigma^2\rho^3 \\
\sigma^2\rho^3 & \sigma^2\rho^2 & \sigma^2\rho^1 & \sigma^2 & \sigma^2\rho^1 & \sigma^2\rho^2 \\
\sigma^2\rho^4 & \sigma^2\rho^3 & \sigma^2\rho^2 & \sigma^2\rho^1 & \sigma^2 & \sigma^2\rho^1 \\
\sigma^2\rho^5 & \sigma^2\rho^4 & \sigma^2\rho^3 & \sigma^2\rho^2 & \sigma^2\rho^1 & \sigma^2
\end{pmatrix}
$$

$$
\boldsymbol{H_1}: \boldsymbol{R} = \begin{pmatrix}
\sigma_1^2 & Cov_{1,2} & Cov_{1,3} & Cov_{1,4} & Cov_{1,5} & Cov_{1,6} \\
Cov_{2,1} & \sigma_2^2 & Cov_{2,3} & Cov_{2,4} & Cov_{2,5} & Cov_{2,6} \\
Cov_{3,1} & Cov_{3,2} & \sigma_3^2 & Cov_{3,4} & Cov_{3,5} & Cov_{3,6} \\
Cov_{4,1} & Cov_{4,2} & Cov_{4,3} & \sigma_4^2 & Cov_{4,5} & Cov_{4,6} \\
Cov_{5,1} & Cov_{5,2} & Cov_{5,3} & Cov_{5,4} & \sigma_5^2 & Cov_{5,6} \\
Cov_{6,1} & Cov_{6,2} & Cov_{6,3} & Cov_{6,4} & Cov_{6,5} & \sigma_6^2
\end{pmatrix}
$$

I compare –2 REML log-likelihood of nested model ($\mathrm{H}_0 - \mathrm{Model\ 3}$) with reference model ($\mathrm{H}_1 - \mathrm{Model\ 4}$). Test statistic is asymptotically distributed by $\chi^2_{df=19}$.

–2 REML log-likelihood of nested model (M3):377155.6
–2 REML log-likelihood of reference model (M4): 375572.8

$$
\begin{aligned}
\chi^2_{df=19} &= \Delta - 2\, REML\ LL = (-2\, LL_{M3}) - (-2\, LL_{M4}) = 377155.6 - 375572.8 \\
&= 1582.8 \\
\chi^2_{df=19,\ critial,\ \alpha=0.0001} &= 50.8
\end{aligned}
$$

Model 4 is preferred over Model 3. Finally, in Model 5, cluster confounding of the first level explanatory variables is addressed.

3.4.6 Model 5

In Model 5, the difference in the within- and between-firm effects of the 1st level variables (i.e. the problem of cluster confounding) is captured through the β^w and β^b coefficients, respectively. The between-firm part is defined as the average value of a particular explanatory variable during the analyzed period, which is calculated for each firm separately, and is denoted as $\bar{X}^b_{ijk}$. After that, the within-firm part is calculated using *Equation 3-13*.

$$
X^w_{tijk} = X_{tijk} - \bar{X}^b_{ijk} \tag{3-13}
$$

The separation of within- and between-firm effect is done for all first level explanatory variables. The full model is written in *Equation 3-14*

$$
\begin{aligned}
&Leverage_{tijk} = \\
&\beta_0 + \beta_1^w \cdot Profitability\,^w_{(t-1)ijk} + \beta_1^b \cdot \overline{Profitability}\,^b_{ijk} + \beta_2^w \cdot \\
&Firm\ size\,^w_{(t-1)ijk} + \beta_2^b \cdot \overline{Firm\ size}^b_{ijk} + \beta_3^w \cdot Firm\ growth\,^w_{(t-1)ijk} + \\
&\beta_3^b \cdot \overline{Firm\ growth}^b_{ijk} + \beta_4^w \cdot Tangibility\,^w_{(t-1)ijk} + \beta_4^b \cdot \\
&\overline{Tangibility}\,^b_{ijk} + \beta_5 \cdot Fin.distress_{ijk} + \beta_6 \cdot Public_{ijk} + \beta_7 \cdot \\
&Unique\ products_{ijk} + \beta_8 \cdot GDP_{(t-1)k} + \beta_9 \cdot Inflation_{(t-1)k} + \beta_{10} \cdot \\
&Tax\ rate_k + u_{0\,k} + r_{0\,j|k} + \varepsilon_{tijk} \\
&u_{0\,k} \sim N\left(0, \sigma^2_{int:\,Country}\right) \quad r_{0\,j|k} \sim N\left(0, \sigma^2_{int:\,Industry}\right) \quad \varepsilon_{tijk} \sim N\left(0, \sigma_t^2\right)
\end{aligned}
\tag{3-14}
$$

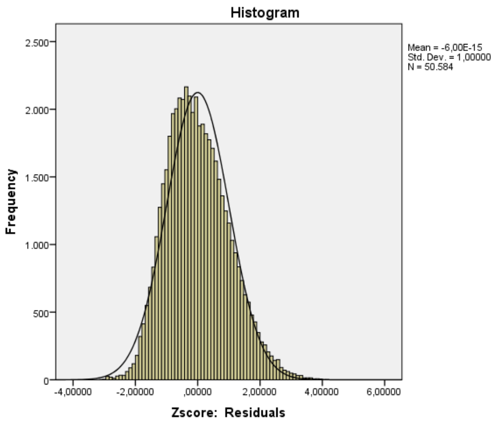
In this specification, $Leverage_{tijk}$ represents the value of the dependent variable in time *t* for firm *i*, operating within industry *j* and country *k*. β_0 is a fixed intercept and β_1 till β_{10} are fixed effect for the first, second and fourth level explanatory variables. $u_{0\,k}$ is the random effect associated with the intercept for country *k*, $r_{0\,j|k}$ is the random effect associated with the intercept for industry *j*, and ε_{tijk} is the residual. The distribution of random effects is assumed to follow normal distribution. $\sigma^2_{int:\,Country}$ represents the variance of the country-specific random intercept, and $\sigma^2_{int:\,Industry}$ represents the variance of the random industry-specific intercepts at any given country. Finally, σ_t^2 represents the residual variance. The full SPSS output of this model is presented in Appendix B-8, while the model is written in *Equation 3-15*.

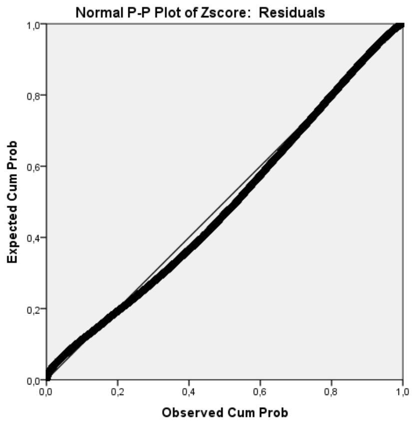
$$
\begin{aligned}
&\widehat{Leverage}_{tijk} = 14.674 - 0.049 \cdot Profitability\,^w_{(t-1)ijk} - 0.253 \cdot \\
&\overline{Profitability}\,^b_{ijk} + 17.801 \cdot Firm\ size\,^w_{(t-1)ijk} + 0.264 \cdot \\
&\overline{Firm\ size}^b_{ijk} + 0.062 \cdot Firm\ growth\,^w_{(t-1)ijk} + 0.071 \cdot \\
&\overline{Firm\ growth}^b_{ijk} + 0.033 \cdot Tangibility\,^w_{(t-1)ijk} + 0.258 \cdot \\
&\overline{Tangibility}\,^b_{ijk} - 0.425 \cdot Fin.distress_{ijk} - 1.501 \cdot Public_{ijk} - 1.402 \cdot \\
&Unique\ products_{ijk} + 0.000 \cdot GDP_{(t-1)k} + 0.160 \cdot Inflation_{(t-1)k} + \\
&0.179 \cdot Tax\ rate_k \\
&u_{0\,k} \sim N\,(0, 67.47) \quad r_{0\,j|k} \sim N\,(0, 43.63) \quad \varepsilon_{tijk} \sim N\,(0, \sigma_t^2)
\end{aligned}
\tag{3-15}
$$

I test whether cluster confounding is present among Level 1 explanatory variables. Both AIC and BIC statistics of Model 5 are lower compared to the values of Model 4 (see Appendix B-8). That means that controlling for cluster confounding of the Level 1 explanatory variables improves the overall fit of the model.

Goodness of fit. The multiple regression model without controlling for any source of dependency shows that 10 covariates explain 16.8 percent of total variability of leverage. However, there is no general agreement on how coefficient of determination in multilevel regression should be estimated (Hox, 2010; Gelman & Hill, 2007; Snijders & Bosker, 2012). It is interesting that there are numerous in-depth works about multilevel regression, which completely ignore the concept of the coefficient of determination (e.g. West et al., 2015; Tabachnick & Fidell, 2012; Field, 2013). Instead, their analysis is concentrated on the analysis of goodness of fit through log-likelihood statistics. This stems from the fact that multilevel regression is typically based on maximum likelihood method, while coefficient of determination belongs to the method of least squares. Through the analysis of goodness of fit I find, as expected, that multilevel regression fits the data significantly better than pooled regression analysis (AIC of pooled regression analysis with controlling for time-series dependency is 378872.1, while AIC of Model 4 which additionally controls for cross-sectional dependency, is reduced to 375618.9). I further analyze how much of leverage heterogeneity is explained by traditional determinants only, without controlling for a hierarchical structure of the data, but still controlling for time-series dependency among observations. Frank and Goyal (2009) performed a comprehensive review of past empirical studies and found that the six main determinants (industry median leverage, tangibility, profits, firm size, market-to-book-assets ratio, and inflation) explained 27 percent of the variation in leverage. Since market-to-book assets ratio is unavailable for my sample, I check the explanatory power of the remaining five covariates and got the reduction of residual variance equal to 17.6 percent, a result very similar to findings of Lemmon et al. (2008).

Figure 3-4. *Histogram of residuals and normal P-P plot*





Source: Bureau van Dijk, *Amadeus database*, 2013.

Finally, I check the distribution of residuals for Model 5 and find that the assumption of normally distributed residuals is well met (*Figure 3-4*).

3.4.7 Comparison of regression models results

In *Table 3-8* I show estimated regression coefficients for the multiple regression model, multiple regression model that is controlled for time-series dependency (standard errors are clustered by firm, see Petersen, 2009), and six multilevel regression models, which also control for the hierarchical structure of the data (allowing intercept to vary freely among third and fourth level units). AIC statistics (Akaike Information Criteria) show that multilevel regression models have a statistically better fit than the multiple regression models.

As expected, more profitable firms have lower leverage, holding all other covariates unchanged. This goes in line with the *pecking order hypothesis* and with the *dynamic trade-off theory*. Each additional percentage point of profitability decreases the expected leverage by 0.05 of a percentage point, controlling for all other covariates (p-value < 0.001). The multiple regression model with standard errors clustered by firm shows no statistically significant effect, while Model 5 reveals that the between-firm effect is stronger, which is supported by the formal test[18] at very high level of significance.

[18] The formal test is performed by modifying *Equation 3-14* in the following way. Instead of using within-firm operationalization of each first level variable, the untransformed variables are used. These untransformed variables still capture the within-firm effects, but the meaning of regression coefficients of between-firm operationalization of these variables is changed. They show whether the differences between the within- and between-firm effects are statistically significant (see Bartels, 2008).

Table 3-8. *Summary of results of regression models*

On a sample of 8,777 firms (50,584 firm-year observations), eight models are estimated. For baseline purposes, the standard (pooled) multiple regression model is fitted and the pooled multiple regression model as a repeated measurement model with AR(1) residual matrix. The six multilevel linear models are fitted with AR(1) or UNR residual matrix, and are controlled for hierarchical structure of the data (firms are nested within industries and within countries). In multilevel linear models 1 to 3, explanatory variables on different levels are gradually included. Model 4 allows for an unstructured residual matrix, which improves the fit of the model. Finally, Model 5 shows the importance of separating the within- and between-firm effects of first-level explanatory variables. Reference and nested models (M0–M4) are compared with –2 log-likelihood statistics that shows the fit of the model – lower value indicates a better fit. All models together are compared with AIC – lower value indicates a better fit.

			Multiple regression		**Multilevel regression**						
	Variable			AR(1)	**M0** AR(1)	**M1** AR(1)	**M2** AR(1)	**M3** AR(1)	**M4** UNR	**M5** UNR W	**M5** UNR B
	SE clustered by firm		No	Yes	Yes						
	Hierarchical structure – allowing a random intercept		No	No	Yes						
	INTERCEPT	β_0	10.142	2.962	27.332	3.738	7.746	5.456	3.464		14.674
Level 1 covariates	PROFITABILITY	β_1	–0.173	–0.010		–0.017	–0.011	–0.016	–0.050	–0.049	–0.253
	Sig. (2-tailed)		*0.000*	*0.260*		*0.055*	*0.185*	*0.060*	*0.000*	*0.000*	*0.000*
	SIZE	β_2	1.172	4.702		4.291	4.265	4.225	4.746	17.801	0.264
	Sig. (2-tailed)		*0.000*	*0.000*		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.424*
	GROWTH	β_3	0.019	0.030		0.028	0.028	0.029	0.030	0.062	0.071
	Sig. (2-tailed)		*0.000*	*0.000*		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
	TANGIBILITY	β_4	0.268	0.136		0.119	0.113	0.114	0.118	0.033	0.258
	Sig. (2-tailed)		*0.000*	*0.000*		*0.000*	*0.000*	*0.000*	*0.000*	*0.000*	*0.000*
Level 2 covariates	FIN. DISTRESS	β_5	–0.742	–0.906			–0.563	–0.562	–0.542		–0.425
	Sig. (2-tailed)		*0.000*	*0.000*			*0.000*	*0.000*	*0.000*		*0.000*
	D_{PUBLIC}	β_6	–2.255	–3.305			–3.117	–3.105	–3.260		–1.501
	Sig. (2-tailed)		*0.000*	*0.000*			*0.000*	*0.000*	*0.000*		*0.002*
	$D_{UNIQUE\ PRODUCTS}$	β_7	–0.856	–2.602			–3.068	–3.064	–3.080		–1.402
	Sig. (2-tailed)		*0.024*	*0.002*			*0.000*	*0.000*	*0.000*		*0.093*

	Variable		Multiple regression		Multilevel regression						
					M0	**M1**	**M2**	**M3**	**M4**	**M5** UNR	
				AR(1)	AR(1)	AR(1)	AR(1)	AR(1)	UNR	W	B
Level 4 covariates	GDP$_{GROWTH}$	β_8	–0.294	0.025				0.035	0.020		0.000
	Sig. (2-tailed)		*0.000*	*0.012*				*0.000*	*0.025*		*0.968*
	INFLATION	β_9	0.590	0.127				0.105	0.146		0.160
	Sig. (2-tailed)		*0.000*	*0.000*				*0.000*	*0.000*		*0.000*
	TAX RATE	β_{10}	0.350	0.219				0.092	0.080		0.179
	Sig. (2-tailed)		*0.000*	*0.000*				*0.718*	*0.763*		*0.494*
	–2 log-likelihood		448,205	378,868	378,142	377,308	377,170	377,115	375,573		374,394
	χ^2		/	/	/	834	138	55	1,583		/
	Sig.		/	/	/	*0.000*	*0.000*	*0.000*	*0.000*		/
	AIC		448,207	378,872	378,150	377,326	377,193	377,145	375,619		374,470

Source: Bureau van Dijk, *Amadeus database*, 2013.

Graham and Leary (2011) surveyed recent empirical studies and found that highly leveraged firms are significantly larger. The main argument goes that larger firms have a lower default risk and consequently have a higher target debt ratio. Model 4 shows that a ten times larger firm, as measured by total assets, has on average a 4.75 percentage point higher leverage, controlling for all other covariates. Arguably, most interesting is the results for Model 5. It shows that the within-firm effect is especially strong, while the between-firm effect is much weaker and statistically insignificant (there is a statistically significant difference between both effects at a very high level of confidence). Specifically, a within-firm increase in total assets of ten times is associated with an average 17.80 percentage point higher leverage, ceteris paribus (*p*-value < 0.001). On the other hand, comparing firms cross-sectionally, a ten times larger firm has on average a higher leverage of only 0.26 of a percentage point, ceteris paribus, however, the result is insignificant. Contrary to the survey conclusion made by Graham and Leary (2011), my results thus show that larger and smaller firms do not differ in their average indebtedness. However, a firm that substantially increases its size also substantially increases its indebtedness. Separating within- and between-firm effects is thus crucial for properly understanding the effect of size on a firm's leverage. Contrary to the majority of past empirical studies, higher growth positively affects expected leverage. The finding is, however, consistent with Toy et al. (1974), who argued that the *pecking order hypothesis* predicts that fast growth needs to be financed externally and debt is the first choice. The result is probably also a reflection of the time period under analysis. At that time, access to bank loans was relatively easy and firms typically financed growth with new debt. For each additional percentage point of growth in total assets, the expected leverage increases by 0.03 of a percentage point, holding all other covariates unchanged (*p*-value < 0.001). Within- and between-firm effects show no statistical difference, although the standardized regression coefficient of the within-firm effect is almost twice as large. Similarly as found in prior studies, tangibility positively affects leverage. Each additional percentage point of tangible assets increases leverage on average by 0.12 of a percentage point, holding all other covariates unchanged (*p*-value < 0.001). In the case of separating effects, the between-firm effect is much stronger (the effects are different at very high level of statistical significance).

The traditional time-variant covariates have a relatively low explanatory power of the observed capital structure (Miller, 1977), so I include some explanatory variables on the firm level. As expected, higher probability of financial distress, measured as variability of EBIT, leads to lower target leverage. Each additional percentage point of variability decreases the expected leverage by 0.54 of a percentage point, ceteris paribus (p-value < 0.001). According to the results, public firms and firms producing unique and durable products are less indebted, ceteris paribus, which goes in line with the findings of Frank and Goyal (2008).

The first explanatory variable at a country level shows that GDP growth is positively related to leverage (p-value = 0.025). As predicted, inflation positively affects leverage: each additional percentage point of inflation is associated with a 0.15 percentage point higher expected leverage, controlling for all other covariates (p-value < 0.001). Finally, both multiple regression models predicts that the nominal tax rate positively affects corporate leverage. Surprisingly, none of the multilevel linear models show a statistically significant relationship. There can be numerous reasons for this outcome. Tax policies are often complicated and therefore hard to proxy with publicly available data (Graham, 2000). Graham (1996) proposed using a special version of marginal tax rate, however, it is difficult to model. When such a version of marginal tax rate is unavailable, Graham proposed using statutory tax rate, as is done herein. More recently, Huizinga et al. (2008) studied 32 European countries over the period from 1994 to 2003 and found that larger firms face international tax incentives, while the current analysis takes the perspective of a domestic-only firm. This can explain why I do not find that the nominal statuary tax rate would statistically impact observed leverage.

3.5 Predicting the target capital structure

Since multilevel regression essentially improves the accuracy of prediction, I try to confirm the hypothesis of Lev and Pekelman (1975), who developed the idea that a firm incurs costs whenever its debt-equity ratio is below or above the target, and that these costs increase with the extent of the deviation from that target. Many researchers argued that excessive leverage negatively affects a firm's performance (e.g. Saffieddine & Titman, 1999; Fama & French, 2002; Jandik & Makhija, 2005; Gonzales, 2013). For example, Opler and Titman

(1994) found that, in times of economic downturn, highly leveraged firms are the first to lose their customers. Furthermore, Tan (2012) argued that the firms in the top leverage decile underperformed in return on equity compared to the rest of the firms. Additionally, he found that crises magnify the negative impact of leverage on a firm's performance. On the other hand, some researchers argued that the market value of a firm can be successfully increased through improved performance by moving from no-debt financing toward moderate leverage (e.g. Muradoglu & Sivaprasad, 2009; Champion 1999). Handlock and James (2002) found that firms prefer debt financing in anticipation of a higher return, which was similarly argued by Lemmon and Zender (2010), who confirmed that debt appears to be preferred over equity, controlling for debt capacity limitations.

However, Graham and Leary (2011) recently argued that even if convergence toward the target capital structure exists, there remains an open question as to which economic forces motivate within-firm movements of leverage. Kortweg (2010) showed that 5.5 percent of a median firm value can be attributed to net benefits of debt, which means that firms that have too low leverage can successfully benefit by moving toward the target. Kortweg continued that net benefits of increased leverage grow for low leveraged firms but start decreasing when indebtedness becomes high, which supports the existence of the target capital structure. Similarly, Binsbergen, Graham, and Yang (2010) found that the net benefit of the optimal financial choice equals on average 3.5 percent of asset value. Recent empirical research on convergence (e.g. Lemmon et al., 2008; Marinšek et al., 2016) shows, that firms do behave as if they converge toward the target capital structure. To determine which economic factors could motivate such behavior, I consider differences in various aspects of a firm’s performance by comparing the optimally indebted firms (close to the estimated target with multilevel model 5) with the under- and over-indebted ones.

Although a large deviation from the target capital structure may be costly, there may be little incentive for firms with moderate leverage to frequently optimize capital structure in a way that corresponds to the changes in the trade-off variables. Furthermore, the importance of capital structure trade-offs may be modest over a wide range of leverage choices, which can explain the low explanatory power of models for explaining capital structure heterogeneity (Graham & Leary, 2011). Binsbergen et al. (2010) showed that in a range of 20 percent above or below the optimal leverage, the firm value function is practically flat. Still, far out-of-equilibrium choices (e.g. using excessive leverage) can have disastrous effects. Similarly, the costly adjustment model is built on the idea that management weighs tax benefits of debt on the one hand, and distress costs of debt on the other, but the firm nonetheless experiences annual shocks to assets value, which moves its capital structure position away from the target. Since constant recapitalization is costly, this implies that instead of an optimal level of leverage, an optimal range is a more realistic assumption (Graham & Leary, 2011).

Because of that, simply regressing the differences between the actual and the target capital structure on various performance ratios is problematic. Instead, my analysis is done in the following way. For each firm I estimate the average leverage (the ratio of total financial debt relative to total assets) over the analyzed period and compare it with the average predicted (target) leverage for that firm, estimated with a multilevel model 5 (*Equation 3-15*). The differences between the average actual and the average target leverage are calculated, and based on these differences, firms are classified into three groups: 25 percent of firms that have the largest positive difference (above-target indebted firms), 50 percent of firms that are the closest to the estimated target (these firms are assumed to be within optimal range), and 25 percent of firms that have the largest negative difference (below-target indebted firms). As a measure of performance, I choose two ratios, one measuring the return for shareholders and another measuring the return for all providers of capital. These are return on equity (ROE – *Equation 3-16*) and return on capital employed (ROCE – *Equation 3-17*). Both are calculated as arithmetic means over the analyzed period for each firm separately.

$$ROE_t = \frac{Net\ income_t}{Equity\ capital_t} \cdot 100 \tag{3-16}$$

Return on equity measures a firm's profitability by analyzing how much profit a firm generates with the money shareholders have invested. Brigham and Daves (2004) wrote that ROE is the single most important accounting ratio of performance.

$$ROCE_t = \frac{EBIT_t}{Equity\ capital_t + Noncurrent\ liabilities_t} \cdot 100 \tag{3-17}$$

Return on capital employed measures the return that a business achieves with the total invested capital, showing the firm's profitability and efficiency. A higher ROCE indicates a more efficient use of capital. Compared to ROE, ROCE provides a better indication of financial performance for firms with a significant amount of debt (CFA Institute, 2012).

Table 3-9 shows that firms within the optimal range of leverage have higher median average ROE and ROCE, compared to overleveraged firms. Underleveraged firms, on the other hand, have higher median average ROE and ROCE, compared to optimally indebted firms. This can be explained by the fact that more profitable firms need less external financing because of high internally generated funds. Lev and Pekelman's hypothesis (1975) is thus only partially confirmed for the sample of European firms – firms which are highly overleveraged compared to the target incurred costs in the form of lower return on equity and lower return on capital employed. In other words, overleveraged firms underperform compared to the group of firms that had leverage within the optimal range.

Table 3-9. *Profitability ratios for three leverage portfolios*

The sample size is 8,777 firms. For the period 2006–2011, the average actual total financial indebtedness of each firm is compared with average target total financial indebtedness, estimated by a multilevel model (*Equation 3-15*). Deviations are estimated and firms are grouped into three portfolios: 25 percent of firms with the largest positive deviation (overleveraged firms), 50 percent of firms with actual leverage closest to the target (optimal range), and 25 percent of firms with the largest negative deviation (underleveraged firms). For each leverage portfolio, first quartile (p25), median (p50), and third quartile (p75) are estimated for two profitability ratios: average ROE and average ROCE, calculated for each firm separately over the period 2006–2011.

	ROE			ROCE		
	p25	p50	p75	p25	p50	p75
Overleveraged	1.90	**9.84**	21.00	5.61	**11.11**	19.56
Optimal range	3.39	**10.22**	20.00	6.12	**12.42**	21.75
Underleveraged	4.77	**12.23**	22.81	7.22	**14.88**	26.53

Source: Bureau van Dijk, *Amadeus database*, 2013.

To confirm the statistical differences in average and median profitability ratios between the three portfolios, two non-parametric tests are performed, as shown in *Table 3-10.* These include Mood's median test and Kruskal-Wallis test, both of which show statistically significant differences. Additionally, all pairs of Mann-Whitney tests of two independent conditions are performed, showing that firms within an optimal range have statistically higher mean rank for both ROE and ROCE, compared to overleveraged firms.

Table 3-10. *Testing differences in profitability of three leverage portfolios*

		> Median	≤ Median	**Mood's median test**	**Kruskal-Wallis test**
ROE	Overleveraged	1049	1137	$\chi^2 = 25.88$	$\chi^2 = 44.11$
	Optimal range	2134	2252	df = 2	df = 2
	Underleveraged	1199	994	$p = 0.000$	$p = 0.000$
ROCE	Overleveraged	910	1172	$\chi^2 = 78.77$	$\chi^2 = 84.61$
	Optimal range	2057	2102	df = 2	df = 2
	Underleveraged	1179	874	$p = 0.000$	$p = 0.000$

		Mean rank	**Mann-Whitney test**	
ROE	Optimal range	3320.3	4645812	$z = -2.04$
	Overleveraged	3218.7		$p = 0.041$
	Optimal range	3198.9	4409852	$z = -5.50$
	Underleveraged	3472.1		$p = 0.000$
	Overleveraged	2074.1	2317022	$z = -6.06$
	Underleveraged	2305.5		$p = 0.000$
ROCE	Optimal range	3182.7	4073024	$z = -3.82$
	Overleveraged	2997.8		$p = 0.000$
	Optimal range	2999.0	3822067	$z = -6.73$
	Underleveraged	3324.3		$p = 0.000$
	Overleveraged	1903.4	3962843	$z = -8.93$
	Underleveraged	2234.9		$p = 0.000$

Source: Bureau van Dijk, *Amadeus database*, 2013.

CONCLUSION

Researchers, publishing in financial journals, rarely apply multilevel regression, although it offers an elegant solution for voided assumption of independency of observations, one of the important characteristics of panel data sets. Even more, the structure of financial data usually suggests, as Thompson (2011) recently argued, that multilevel regression would be more appropriate than other regression techniques, if not even required, since firms are nested within industries and countries, which causes a high cross-sectional dependency. Gelman (2006) argued that compared to other regression techniques, multilevel regression essentially improves the accuracy of model predictions. Since predicted targets are often used in various financial studies, multilevel regression should be an attractive statistical method. Two other important benefits of multilevel regression, very useful for financial studies, are that model is not affected by missing longitudinal observations, and that the technique gives efficient predictions also for the firm–industry–country combinations with a small number of observations. I also show that exploring the presence of cluster confounding is critically important to correctly describe any financial topic, analyzed by various regression techniques.

The main empirical finding of applying multilevel regression to the case of corporate capital structure is that the high intraclass correlation of firms, operating in the same industry and country, shows, that there is a high cross-sectional dependency and it is thus important to control for data hierarchy. To support that finding, non-parametric tests are used and they show that there are statistically significant differences in average and median indebtedness across industries and countries, which means that the random intercept model (i.e. multilevel regression) is needed. All in all, the overall fit of the model statistically significantly improves under multilevel settings – multilevel models fit the data statistically significantly better than the typical OLS regression models. The reason can be found in the high importance of controlling for industry (and country) differences in indebtedness, because many researchers demonstrated that industry median leverage is the strongest explanatory variable of capital structure heterogeneity. Additionally, I confirm that separating within- and between-firm effects is crucial for correct understanding of the true impact of various explanatory variables. I believe that multilevel regression and cluster confounding can successfully be applied to many other financial and economic studies, which use such type of data.

Frank and Goyal (2009) presented a comprehensive review of determinants, which have significant power at explaining the observed capital structure heterogeneity of American firms. They found that industry median leverage, tangibility, profitability, firm size, and inflation are among the most reliable factors. I find that all of these factors have statistically significant explanation power also for European firms.[19] I show that profitability has a stronger between-firm effect, which means that more profitable firms need less external financial support. I demonstrate that without separating within- and between-firm size effects, conclusions are extremely misleading. I show that when comparing firms cross-sectionally by their average size (the between-firm effect), there are no differences in indebtedness. On the other hand, the within-firm increase in size reveals substantial leveraging – firms' expansions are largely financed with new debt. I further demonstrate that stronger growth needs additional external financing (preferring debt over new equity), and that tangibility has a much stronger between-firm effect. That proves the importance of the average share of tangible assets: firms that operate with a higher share of tangible assets are able to obtain more debt. I find that firms with a higher variability of operating income are supplied with less debt financing, and that public firms and firms producing unique products use less leverage. I show that management is more inclined to take new debt in times of stronger GDP growth and during periods of high inflation. Contrary to the results of the multiple regression model, multilevel regression shows that the nominal corporate tax rate does not explain differences in the indebtedness of European firms. In addition to the high importance of controlling for industry differences in indebtedness, as for example argued by Lemmon et al. (2008), I find that between-firm tangibility, within-firm size, between-firm profitability, probability of financial distress and within-firm growth are the strongest explanatory variables of the observed capital structure of European firms (compared using standardized partial regression coefficients). Within-firm profitability, between-firm size, between-firm growth, and within-firm tangibility show lower or insignificant explanatory power.

[19] Industry median leverage is modeled through a random intercept at the industry level.

To summarize, results show that compared to the multiple regression model, the multilevel regression exhibits a statistically superior fit when someone uses panel data sets. Moreover, there is a high importance of separating within- and between-group effects of predictors, which are used in various economic studies. In a highly meaningful sense, my capital structure example gives an important “proof of concept”, that points to the likely successful application of the multilevel technique across a broad range of similar corporate finance research settings.

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APPENDICES

LIST OF APPENDICES

Appendix A: R-codes

A-1: Balance sheet structure

```
DrawBalaceSheet <- function(x, my.baza) {

  baza.subset <- droplevels(my.baza[my.baza$Country %in% x, c("FA_ofTA",
"TangFA_ofFA", "CA_ofTA", "Stocks_ofCA","Debtors_ofCA", "Capital_ofTA",
"LTDebt_ofTA", "OthLTLiab_ofTA", "Loans_ofTA", "Payables_ofTA",
"TotFinDebt_ofTA", "Time")])
  baza.subset$Time<-as.factor(baza.subset$Time)
  baza.subset <- melt(baza.subset)

  dummy <- unique(baza.subset[, c("variable", "Time")])
  dummy$value <- 1

  ggplot(baza.subset, aes(x = Time, y = value)) +
    theme_bw()+
    theme(axis.text.x = element_text(angle = 90)) +
    labs(x = "Years", y = "") +
    geom_rect(data = dummy, xmin = -Inf, xmax = Inf, ymin = -Inf, ymax =
Inf,
              alpha = 0.02, show_guide = FALSE) +
    geom_boxplot()+
    scale_y_continuous(limits=c(-0.2,1.0))+
    facet_grid(   ~ variable , scales = "free")
}

DrawBalaceSheet (x="all", my.baza=baza)
```

Appendix B: Multilevel regression

B-1: Multiple regression model – without controlling for time-series dependency

```
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COEFF OUTS R ANOVA COLLIN TOL
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Financial leverage
  /METHOD=ENTER Profitability Firm size Firm's growth Tangibility Risk
Public Uniqueness
   GDP growth Inflation Tax rate
  /RESIDUALS HISTOGRAM(ZRESID) NORMPROB(ZRESID).
```

Model Summary

R	R^2	Adj. R^2	s_e
.409	.168	.167	20.307

ANOVA

	Sum of Squares	df	Mean Square	F	P
Regression	4196039.499	10	419603.950	1017.567	.000
Residual	20854289.315	50573	412.360		
Total	25050328.815	50583			

Coefficients

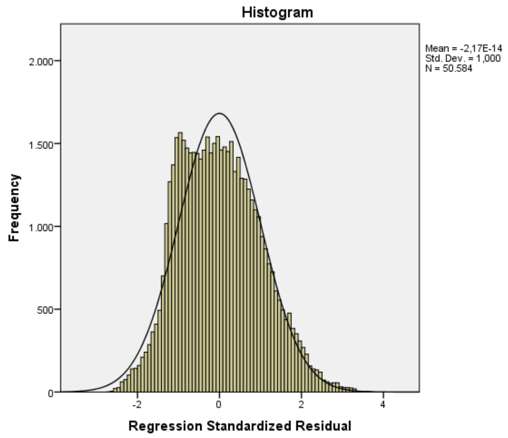
	$\widehat{\beta}$	se($\widehat{\beta}$)	Standardized $\widehat{\beta}$	t	P	Tolerance	VIF
Constant	10.142	.800		12.676	.000		
Profitability	-.173	.015	-.051	-11.758	.000	.885	1.130
Firm size	1.172	.138	.036	8.523	.000	.931	1.074
Firm's growth	.019	.004	.018	4.337	.000	.960	1.042
Tangibility	.268	.003	.340	80.136	.000	.916	1.091
Financial distress	-.742	.033	-.102	-22.812	.000	.831	1.204
Public	-2.255	.195	-.049	-11.583	.000	.936	1.068
Uniqueness	-.856	.379	-.009	-2.261	.024	.988	1.012
GDP growth	-.294	.024	-.051	-12.088	.000	.918	1.089
Inflation	.590	.052	.051	11.310	.000	.802	1.246
Tax rate	.350	.016	.102	22.372	.000	.797	1.254

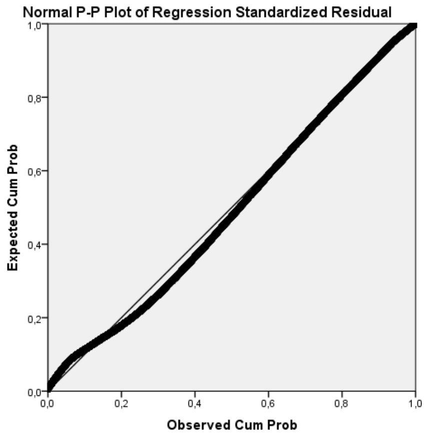
Information Criteria

-2 Log Likelihood	448205.321
Akaike's Information Criterion (AIC)	448207.321
Hurvich and Tsai's Criterion (AICC)	448207.321
Bozdogan's Criterion (CAIC)	448217.152
Schwarz's Bayesian Criterion (BIC)	448216.152

The information criteria are displayed in smaller-is-better form.
Dependent variable: Financial leverage

Histogram of residuals and normal P-P plot





Source: Amadeus, 2013.

B-2: Multiple regression model – with controlling for time-series dependency (standard errors clustered by firm)

```
MIXED Financial leverage WITH Profitability Firm size Firm growth
Tangibility Fin. distress Public Unique products GDP growth Inflation Tax
rate
  /CRITERIA=CIN(95) MXITER(100) MXSTEP(10) SCORING(1)
SINGULAR(0.000000000001) HCONVERGE(0, ABSOLUTE) LCONVERGE(0, ABSOLUTE)
PCONVERGE(0.000001, ABSOLUTE)
  /FIXED= Profitability Firm size Firm growth Tangibility Fin. distress
Public Unique products GDP growth Inflation Tax rate | SSTYPE(3)
  /METHOD=REML
  /PRINT=SOLUTION TESTCOV
  /REPEATED=Time | SUBJECT(Firm*Industry*Country) COVTYPE(AR1).
```

Mixed Model Analysis

Model Dimension

		Number of Levels	Covariance structure	Number of Parameters	Subject Variables	Number of subjects
Fixed Effects	Intercept	1		1		
	Profitability	1		1		
	Firm size	1		1		
	Firm gro.	1		1		
	Tangibility	1		1		
	Fin. distress	1		1		
	Public	1		1		
	Unique.	1		1		
	GDP	1		1		
	Inflation	1		1		
	Tax rate	1		1		
Repeated Effects	Time	6	AR(1)	2	Country*Industry*Firm	8777
Total		17		13		

Dependent variable: Financial leverage

Information Criteria

-2 Log Likelihood	378868.121
Akaike's Information Criterion (AIC)	378872.121
Hurvich and Tsai's Criterion (AICC)	378872.121
Bozdogan's Criterion (CAIC)	378891.783
Schwarz's Bayesian Criterion (BIC)	378889.783

The information criteria are displayed in smaller-is-better form.
Dependent variable: Financial leverage

Type III Tests of Fixed Effects

Source	Numerator df	Denominator df	F	P
Intercept	1	10904.994	3.819	.051
Profitability	1	43524.046	1.267	.260
Firm size	1	12395.547	288.457	.000
Firm growth	1	47846.716	300.998	.000
Tangibility	1	29312.726	652.019	.000
Financial distress	1	9087.301	196.827	.000
Public	1	8512.111	58.461	.000
Uniqueness	1	8552.689	9.847	.002
GDP	1	39425.728	6.264	.012
Inflation	1	39626.377	34.395	.000
Tax rate	1	8573.143	45.391	.000

Dependent variable: Financial leverage

Estimates of Fixed Effects

Source	Estimates	Std. Error	df	t	P	Std. Estimates
Intercept	2.962398	1.515875	10904.994	1.954	.051	
Profitability	-.009819	.008723	43524.046	-1.126	.260	-.002885
Firm size	4.702231	.276862	12395.547	16.984	.000	.143757
Firm growth	.029895	.001723	47846.716	17.349	.000	.028134
Tangibility	.135613	.005311	29312.726	25.535	.000	.171577
Financial distress	-.905510	.064543	9087.301	-14.030	.000	-.123984
Public	-3.304749	.432222	8512.111	-7.646	.000	-.071191
Uniqueness	-2.602168	.829239	8552.689	-3.138	.002	-.028038
GDP	.024809	.009913	39425.728	2.503	.012	.004324
Inflation	.126866	.021632	39626.377	5.865	.000	.011010
Tax rate	.218653	.032454	8573.143	6.737	.000	.063543

Dependent variable: Financial leverage

Estimates of Covariance Parameters

Parameter		Estimates	Std. Error	Wald Z	P
Repeated Measures	**AR1 diagonal**	438.937272	5.651100	77.673	.000
	AR1 ρ	.908056	.001314	690.882	.000

Dependent variable: Financial leverage

B-3: Multilevel model - Model 0

```
MIXED Financial leverage
  /CRITERIA=CIN(95) MXITER(100) MXSTEP(10) SCORING(1)
SINGULAR(0.000000000001) HCONVERGE(0, ABSOLUTE) LCONVERGE(0, ABSOLUTE)
PCONVERGE(0.000001, ABSOLUTE)
  /FIXED=| SSTYPE(3)
  /METHOD=REML
  /PRINT=SOLUTION TESTCOV
  /RANDOM=INTERCEPT | SUBJECT(Country*Industry) COVTYPE(UN)
  /RANDOM=INTERCEPT | SUBJECT(Country) COVTYPE(UN)
  /REPEATED=Time | SUBJECT(Firm*Industry*Country) COVTYPE(AR1).
```

Mixed Model Analysis

Model Dimension

		Number of Levels	Covariance structure	Number of Parameters	Subject Variables	Number of subjects
Fixed Effects	Intercept	1		1		
Random Effects	Intercept	1	Variance Components	1	Country*Industry	
	Intercept	1	Variance Components	1	Country	
Repeated Effects	Time	6	AR(1)	2	Country*Industry*Firm	8777
Total		9		5		

Dependent variable: Financial leverage

Information Criteria

-2 Log Likelihood	378141.576
Akaike's Information Criterion (AIC)	378149.576
Hurvich and Tsai's Criterion (AICC)	378149.577
Bozdogan's Criterion (CAIC)	378188.902
Schwarz's Bayesian Criterion (BIC)	378184.902

The information criteria are displayed in smaller-is-better form.
Dependent variable: Financial leverage

Type III Tests of Fixed Effects

Source	Numerator df	Denominator df	F	P
Intercept	1	22.887	240.944	.000

Dependent variable: Financial leverage

Estimates of Fixed Effects

Source	Estimates	Std. Error	df	t	P
Intercept	27.332435	1.760842	22.887	15.522	.000

Dependent variable: Financial leverage

Estimates of Covariance Parameters

Parameter		Estimates	Std. Error	Wald Z	P
Repeated Measures	**AR1 diagonal**	384.001017	4.770959	80.487	.000
	AR1 ρ	.894248	.001441	620.787	.000
Intercept (subject = Industry*Country)	**Variance**	95.040448	11.427017	8.317	.000
Intercept (subject = Country)	**Variance**	65.714687	22.849487	2.876	.004

Dependent variable: Financial leverage

B-4: Multilevel model - Model 1

```
MIXED Financial leverage WITH Profitability Firm size Firm growth
Tangibility
  /CRITERIA=CIN(95) MXITER(100) MXSTEP(10) SCORING(1)
SINGULAR(0.000000000001) HCONVERGE(0, ABSOLUTE) LCONVERGE(0, ABSOLUTE)
PCONVERGE(0.000001, ABSOLUTE)
  /FIXED= Profitability Firm size Firm growth Tangibility | SSTYPE(3)
  /METHOD=ML
  /PRINT=SOLUTION TESTCOV
  /RANDOM=INTERCEPT | SUBJECT(Country*Industry) COVTYPE(UN)
  /RANDOM=INTERCEPT | SUBJECT(Country) COVTYPE(UN)
  /REPEATED=Time | SUBJECT(Firm*Industry*Country) COVTYPE(AR1).
```

Mixed Model Analysis

Model Dimension

		Number of Levels	Covariance structure	Number of Parameters	Subject Variables	Number of subjects
Fixed Effects	Intercept	1		1		
	Profitability	1		1		
	Firm size	1		1		
	Firm's growth	1		1		
	Tangibility	1		1		
Random Effects	Intercept	1	Variance Components	1	Country*Industry	
	Intercept	1	Variance Components	1	Country	
Repeated Effects	Time	6	AR(1)	2	Country*Industry*Firm	8777
Total		13		9		

Dependent variable: Financial leverage

Information Criteria

-2 Log Likelihood	377307.665
Akaike's Information Criterion (AIC)	377325.665
Hurvich and Tsai's Criterion (AICC)	377325.669
Bozdogan's Criterion (CAIC)	377414.148
Schwarz's Bayesian Criterion (BIC)	377405.148

The information criteria are displayed in smaller-is-better form.
Dependent variable: Financial leverage

Type III Tests of Fixed Effects

Source	Numerator df	Denominator df	F	P
Intercept	1	59.168	3.188	.079
Profitability	1	44251.696	3.680	.055
Firm size	1	12806.779	225.792	.000
Firm growth	1	47993.462	265.040	.000
Tangibility	1	32006.954	457.782	.000

Dependent variable: Financial leverage

Estimates of Fixed Effects

Source	Estimates	Std. Error	df	t	P	Std. Estimates
Intercept	3.737852	2.093380	59.168	1.786	.079	
Profitability	-.016575	.008641	44251.696	-1.918	.055	-.004869
Firm size	4.291367	.285589	12806.779	15.026	.000	.131196
Firm growth	.027983	.001719	47993.462	16.280	.000	.026335
Tangibility	.119495	.005585	32006.954	21.396	.000	.151184

Dependent variable: Financial leverage

Estimates of Covariance Parameters

Parameter		Estimates	Std. Error	Wald Z	P
Repeated Measures	**AR1 diagonal**	365.178731	4.608205	79.245	.000
	AR1 ρ	.889428	.001544	576.022	.000
Intercept (subject = Industry*Country)	**Variance**	69.808731	9.104203	7.668	.000
Intercept (subject = Country)	**Variance**	60.257737	20.081949	3.001	.003

Dependent variable: Financial leverage

B-5: Multilevel model - Model 2

```
MIXED Financial leverage WITH Profitability Firm size Firm growth
Tangibility Fin. distress Public Unique products
  /CRITERIA=CIN(95) MXITER(100) MXSTEP(10) SCORING(1)
SINGULAR(0.000000000001) HCONVERGE(0, ABSOLUTE) LCONVERGE(0, ABSOLUTE)
PCONVERGE(0.000001, ABSOLUTE)
  /FIXED= Profitability Firm size Firm growth Tangibility Fin. distress
Public Unique products | SSTYPE(3)
  /METHOD=ML
  /PRINT=SOLUTION TESTCOV
  /RANDOM=INTERCEPT | SUBJECT(Country*Industry) COVTYPE(UN)
  /RANDOM=INTERCEPT | SUBJECT(Country) COVTYPE(UN)
  /REPEATED=Time | SUBJECT(Firm*Industry*Country) COVTYPE(AR1).
```

Mixed Model Analysis

Model Dimension

		Number of Levels	Covariance structure	Number of Parameters	Subject Variables	Number of subjects
Fixed Effects	Intercept	1		1		
	Profitability	1		1		
	Firm size	1		1		
	Firm gro.	1		1		
	Tangibility	1		1		
	Fin. distress	1		1		
	Public	1		1		
	Unique	1		1		
Random Effects	Intercept	1	Variance Components	1	Country*Industry	
	Intercept	1	Variance Components	1	Country	
Repeated Effects	Time	6	AR(1)	2	Country*Industry*Firm	8777
Total		16		12		

Dependent variable: Financial leverage

Information Criteria

-2 Log Likelihood	377169.471
Akaike's Information Criterion (AIC)	377193.471
Hurvich and Tsai's Criterion (AICC)	377193.477
Bozdogan's Criterion (CAIC)	377311.447
Schwarz's Bayesian Criterion (BIC)	377299.447

The information criteria are displayed in smaller-is-better form.
Dependent variable: Financial leverage

Type III Tests of Fixed Effects

Source	Numerator df	Denominator df	F	P
Intercept	1	62.282	12.883	.001
Profitability	1	43945.055	1.756	.185
Firm size	1	13102.589	213.920	.000
Firm growth	1	48160.409	264.882	.000
Tangibility	1	32378.685	409.126	.000
Financial distress	1	9188.363	83.019	.000
Public	1	8659.029	40.631	.000
Unique products	1	8646.597	13.695	.000

Dependent variable: Financial leverage

Estimates of Fixed Effects

Source	Estimates	Std. Error	df	t	P	Std. Estimates
Intercept	7.745654	2.158011	62.282	3.589	.001	
Profitability	-.011471	.008656	43945.055	-1.325	.185	-.003370
Firm size	4.265166	.291615	13102.589	14.626	.000	.130395
Firm growth	.028043	.001723	48160.409	16.275	.000	.026392
Tangibility	.113380	.005605	32378.685	20.227	.000	.143447
Financial distress	-.563286	.061822	9188.363	-9.111	.000	-.077126
Public	-3.116724	.488956	8659.029	-6.374	.000	-.067141
Unique products	-3.067998	.829025	8646.597	-3.701	.000	-.033057

Dependent variable: Financial leverage

Estimates of Covariance Parameters

Parameter		Estimates	Std. Error	Wald Z	P
Repeated Measures	**AR1 diagonal**	361.888287	4.553429	79.476	.000
	AR1 ρ	.888492	.001552	572.514	.000
Intercept (subject = Industry*Country)	**Variance**	64.627200	8.576682	7.535	.000
Intercept (subject = Country)	**Variance**	62.847088	20.791415	3.023	.003

Dependent variable: Financial leverage

B-6: Multilevel model - Model 3

```
MIXED Financial leverage WITH Profitability Firm size Firm growth
Tangibility Fin. distress Public Unique products GDP growth Inflation Tax
rate
  /CRITERIA=CIN(95) MXITER(100) MXSTEP(10) SCORING(1)
SINGULAR(0.000000000001) HCONVERGE(0, ABSOLUTE) LCONVERGE(0, ABSOLUTE)
PCONVERGE(0.000001, ABSOLUTE)
  /FIXED= Profitability Firm size Firm growth Tangibility Fin. distress
Public Unique products GDP growth Inflation Tax rate | SSTYPE(3)
  /METHOD=ML
  /PRINT=SOLUTION TESTCOV
  /RANDOM=INTERCEPT | SUBJECT(Country*Industry) COVTYPE(UN)
  /RANDOM=INTERCEPT | SUBJECT(Country) COVTYPE(UN)
  /REPEATED=Time | SUBJECT(Firm*Industry*Country) COVTYPE(AR1).
```

Mixed Model Analysis

Model Dimension

		Number of Levels	Covariance structure	Number of Parameters	Subject Variables	Number of subjects
Fixed Effects	Intercept	1		1		
	Profitability	1		1		
	Firm size	1		1		
	Firm gro.	1		1		
	Tangibility	1		1		
	Fin. distress	1		1		
	Public	1		1		
	Unique	1		1		
	GDP	1		1		
	Inflation	1		1		
	Tax rate	1		1		
Random Effects	Intercept	1	Variance Components	1	Country*Industry	
	Intercept	1	Variance Components	1	Country	
Repeated Effects	Time	6	AR(1)	2	Country*Industry*Firm	8777
Total		19		15		

Dependent variable: Financial leverage

Information Criteria

-2 Log Likelihood	377114.522
Akaike's Information Criterion (AIC)	377144.522
Hurvich and Tsai's Criterion (AICC)	377144.531
Bozdogan's Criterion (CAIC)	377291.993
Schwarz's Bayesian Criterion (BIC)	377276.993

The information criteria are displayed in smaller-is-better form.
Dependent variable: Financial leverage

Type III Tests of Fixed Effects

Source	Numerator df	Denominator df	F	P
Intercept	1	25.943	.814	.375
Profitability	1	43971.708	3.536	.060
Firm size	1	13080.377	209.864	.000
Firm growth	1	48084.029	287.130	.000
Tangibility	1	32252.940	414.612	.000
Financial distress	1	9194.487	82.574	.000
Public	1	8667.837	40.349	.000
Uniqueness	1	8653.612	13.671	.000
GDP	1	38835.553	12.317	.000
Inflation	1	38551.455	23.310	.000
Tax rate	1	23.042	.133	.718

Dependent variable: Financial leverage

Estimates of Fixed Effects

Source	Estimates	Std. Error	df	t	P	Std. Estimates
Intercept	5.455702	6.046768	25.943	.902	.375	
Profitability	-.016360	.008700	43971.708	-1.881	.060	-.004806
Firm size	4.224506	.291613	13080.377	14.487	.000	.129152
Firm growth	.029373	.001733	48084.029	16.945	.000	.027643
Tangibility	.114254	.005611	32252.940	20.362	.000	.144554
Financial distress	-.561725	.061816	9194.487	-9.087	.000	-.076912
Public	-3.104729	.488776	8667.837	-6.352	.000	-.066882
Uniqueness	-3.063917	.828646	8653.612	-3.697	.000	-.033013
GDP	.034946	.009957	38835.553	3.510	.000	.006090
Inflation	.105162	.021781	38551.455	4.828	.000	.009127
Tax rate	.091921	.251602	23.042	.365	.718	.026713

Dependent variable: Financial leverage

Estimates of Covariance Parameters

Parameter		Estimates	Std. Error	Wald Z	P
Repeated Measures	**AR1 diagonal**	361.540659	4.547647	79.501	.000
	AR1 ρ	.888509	.001551	572.854	.000
Intercept (subject = Industry*Country)	**Variance**	64.449726	8.561965	7.527	.000
Intercept (subject = Country)	**Variance**	62.191450	20.641583	3.013	.003

Dependent variable: Financial leverage

B-7: Multilevel model - Model 4

```
MIXED Financial leverage WITH Profitability Firm size Firm growth
Tangibility Fin. distress Public Unique products GDP growth Inflation Tax
rate
  /CRITERIA=CIN(95) MXITER(100) MXSTEP(10) SCORING(1)
SINGULAR(0.000000000001) HCONVERGE(0, ABSOLUTE) LCONVERGE(0, ABSOLUTE)
PCONVERGE(0.000001, ABSOLUTE)
  /FIXED= Profitability Firm size Firm growth Tangibility Fin. distress
Public Unique products GDP growth Inflation Tax rate | SSTYPE(3)
  /METHOD=REML
  /PRINT=SOLUTION TESTCOV
  /RANDOM=INTERCEPT | SUBJECT(Country*Industry) COVTYPE(UN)
  /RANDOM=INTERCEPT | SUBJECT(Country) COVTYPE(UN)
  /REPEATED=Time | SUBJECT(Firm*Industry*Country) COVTYPE(UNR).
```

Mixed Model Analysis

Model Dimension

		Number of Levels	Covariance structure	Number of Parameters	Subject Variables	Number of subjects
Fixed Effects	Intercept	1		1		
	Profitability	1		1		
	Firm size	1		1		
	Firm gro.	1		1		
	Tangibility	1		1		
	Fin. distress	1		1		
	Public	1		1		
	Unique.	1		1		
	GDP	1		1		
	Inflation	1		1		
	Tax rate	1		1		
Random Effects	Intercept	1	Variance Components	1	Country*Industry	
	Intercept	1	Variance Components	1	Country	
Repeated Effects	Time	6	Unstructured correlations	21	Country*Industry*Firm	8777
Total		19		34		

Dependent variable: Financial leverage

Information Criteria

-2 Log Likelihood	375572.818
Akaike's Information Criterion (AIC)	375618.818
Hurvich and Tsai's Criterion (AICC)	375618.840
Bozdogan's Criterion (CAIC)	375844.935
Schwarz's Bayesian Criterion (BIC)	375821.935

The information criteria are displayed in smaller-is-better form.
Dependent variable: Financial leverage

Type III Tests of Fixed Effects

Source	Numerator df	Denominator df	F	P
Intercept	1	23.824	.301	.588
Profitability	1	40348.978	33.273	.000
Firm size	1	14120.540	262.348	.000
Firm growth	1	41428.061	288.053	.000
Tangibility	1	32930.998	449.717	.000
Financial distress	1	8789.132	72.932	.000
Public	1	8343.143	41.728	.000
Uniqueness	1	8310.904	12.963	.000
GDP	1	10839.470	5.058	.025
Inflation	1	16804.428	47.873	.000
Tax rate	1	21.336	.093	.763

Dependent variable: Financial leverage

Estimates of Fixed Effects

Source	Estimates	Std. Error	df	t	P	Std. Estimates
Intercept	3.464404	6.314159	23.824	.549	.588	
Profitability	-.049852	.008642	40348.978	-5.768	.000	-.014646
Firm size	4.746122	.293022	14120.540	16.197	.000	.145099
Firm growth	.030354	.001788	41428.061	16.972	.000	.028566
Tangibility	.118100	.005569	32930.998	21.207	.000	.149420
Financial distress	-.542344	.063506	8789.132	-8.540	.000	-.074259
Public	-3.259639	.504607	8343.143	-6.460	.000	-.070219
Uniqueness	-3.079603	.855358	8310.904	-3.600	.000	-.033182
GDP	.020417	.009078	10839.470	2.249	.025	.003558
Inflation	.146083	.021113	16804.428	6.919	.000	.012678
Tax rate	.080243	.263287	21.336	.305	.763	.023319

Dependent variable: Financial leverage

Estimates of Covariance Parameters

Parameter		Estimates	Std. Error	Wald Z	P
Repeated Measures	**Var (1)**	374.725965	6.033480	62.108	.000
	Var (2)	376.755984	5.986124	62.938	.000
	Var (3)	381.087304	6.028029	63.219	.000
	Var (4)	362.864857	5.704983	63.605	.000
	Var (5)	348.988170	5.499087	63.463	.000
	Var (6)	346.114030	5.474117	63.227	.000
	Corr (2,1)	.876155	.002652	330.415	.000
	Corr (3,1)	.793344	.004226	187.711	.000
	Corr (3,2)	.873483	.002656	328.828	.000
	Corr (4,1)	.743564	.005087	146.162	.000
	Corr (4,2)	.805381	.003953	203.762	.000
	Corr (4,3)	.880837	.002513	350.483	.000
	Corr (5,1)	.711905	.005607	126.966	.000
	Corr (5,2)	.766822	.004625	165.795	.000
	Corr (5,3)	.828129	.003532	234.478	.000
	Corr (5,4)	.903377	.002048	441.158	.000
	Corr (6,1)	.685630	.006017	113.947	.000
	Corr (6,2)	.726758	.005300	137.116	.000
	Corr (6,3)	.784119	.004312	181.867	.000
	Corr (6,4)	.850417	.003099	274.380	.000

Parameter		Estimates	Std. Error	Wald Z	P
	Corr (6,5)	.916141	.001794	510.571	.000
Intercept (subject = Industry*Country)	**Variance**	61.183139	8.329233	7.346	.000
Intercept (subject = Country)	**Variance**	68.968067	23.489904	2.936	.003

B-8: Multilevel model - Model 5

```
MIXED Financial leverage WITH Profitability W Profitability B Firm size W
Firm size B Firm growth W Firm growth B Tangibility W Tangibility B Fin.
distress Public Unique products GDP growth Inflation Tax rate
  /CRITERIA=CIN(95) MXITER(100) MXSTEP(10) SCORING(1)
SINGULAR(0.000000000001) HCONVERGE(0, ABSOLUTE) LCONVERGE(0, ABSOLUTE)
PCONVERGE(0.000001, ABSOLUTE)
  /FIXED= Profitability W Profitability B Firm size W Firm size B Firm
growth W Firm growth B Tangibility W Tangibility B Fin. distress Public
Unique products GDP growth Inflation Tax rate | SSTYPE(3)
  /METHOD=ML
  /PRINT=SOLUTION TESTCOV
  /RANDOM=INTERCEPT | SUBJECT(Country*Industry) COVTYPE(UN)
  /RANDOM=INTERCEPT | SUBJECT(Country) COVTYPE(UN)
  /REPEATED=Time | SUBJECT(Firm*Industry*Country) COVTYPE(UNR).
```

Mixed Model Analysis

Model Dimension

		Number of Levels	Covariance structure	Number of Parameters	Subject Variables	Number of subjects
Fixed Effects	Intercept	1		1		
	Prof. W	1		1		
	Prof. B	1		1		
	Firm s. W	1		1		
	Firm s. B	1		1		
	Firm g. W	1		1		
	Firm g. B	1		1		
	Tangib. W	1		1		
	Tangib. B	1		1		
	Fin. distress	1		1		
	Public	1		1		
	Unique.	1		1		
	GDP	1		1		
	Inflation	1		1		
	Tax rate	1		1		
Random Effects	Intercept	1	Variance Components	1	Country*Industry	
	Intercept	1	Variance Components	1	Country	
Repeated Effects	Time	6	Unstructured correlations	21	Country*Industry*Firm	8777
Total		23		38		

Dependent variable: Financial leverage

Information Criteria

-2 Log Likelihood	374394.358
Akaike's Information Criterion (AIC)	374470.358
Hurvich and Tsai's Criterion (AICC)	374470.417
Bozdogan's Criterion (CAIC)	374843.951
Schwarz's Bayesian Criterion (BIC)	374805.951

The information criteria are displayed in smaller-is-better form.
Dependent variable: Financial leverage

Type III Tests of Fixed Effects

Source	Numerator df	Denominator df	F	P
Intercept	1	26.891	5.540	.026
Profitability W	1	37303.413	30.764	.000
Profitability B	1	8746.357	43.831	.000
Firm size W	1	23354.006	939.243	.000
Firm size B	1	8687.695	.639	.424
Firm growth W	1	40987.513	849.939	.000
Firm growth B	1	8938.724	12.702	.000
Tangibility W	1	38569.582	22.065	.000
Tangibility B	1	7388.022	896.109	.000
Financial distress	1	9018.428	42.014	.000
Public	1	8672.952	9.214	.002
Uniqueness	1	8757.043	2.814	.093
GDP	1	10917.537	.002	.968
Inflation	1	16904.444	58.460	.000
Tax rate	1	23.342	.483	.494

Dependent variable: Financial leverage

Estimates of Fixed Effects

Source	Estimates	Std. Error	df	t	P	Std. Estimates
Intercept	14.674450	6.234322	26.891	2.354	.026	
Profitability W	-.048718	.008783	37303.413	-5.547	.000	-.008457
Profitability B	-.253430	.038280	8746.357	-6.620	.000	-.059977
Firm size W	17.800548	.580824	23354.006	30.647	.000	.075961
Firm size B	.263695	.329821	8687.695	.800	.424	.007988
Firm growth W	.061626	.002114	40987.513	29.154	.000	.051868
Firm growth B	.070673	.019830	8938.724	3.564	.000	.029758
Tangibility W	.033425	.007116	38569.582	4.697	.000	.008670
Tangibility B	.257721	.008609	7388.022	29.935	.000	.317975
Financial distress	-.425294	.065613	9018.428	-6.482	.000	-.058232
Public	-1.501107	.494533	8672.952	-3.035	.002	-.032337
Uniqueness	-1.402326	.835951	8757.043	-1.678	.093	-.015110
GDP	.000356	.009004	10917.537	.040	.968	.000062
Inflation	.160439	.020984	16904.444	7.646	.000	.013924
Tax rate	.179279	.257932	23.342	.695	.494	.052100

Dependent variable: Financial leverage

Estimates of Covariance Parameters

Parameter		Estimates	Std. Error	Wald Z	P
Repeated Measures	**Var (1)**	356.977663	5.671392	62.944	.000
	Var (2)	358.242883	5.609594	63.863	.000
	Var (3)	363.239511	5.678141	63.972	.000
	Var (4)	346.042109	5.365300	64.496	.000
	Var (5)	334.663167	5.197373	64.391	.000
	Var (6)	335.017596	5.238955	63.947	.000
	Corr (2,1)	.873655	.002663	328.109	.000
	Corr (3,1)	.791482	.004195	188.685	.000
	Corr (3,2)	.869281	.002705	321.360	.000
	Corr (4,1)	.738844	.005084	145.324	.000
	Corr (4,2)	.799824	.003993	200.285	.000
	Corr (4,3)	.877624	.002541	345.368	.000
	Corr (5,1)	.705045	.005619	125.471	.000
	Corr (5,2)	.759715	.004674	162.528	.000
	Corr (5,3)	.822711	.003588	229.302	.000
	Corr (5,4)	.899762	.002097	429.090	.000
	Corr (6,1)	.674167	.006099	110.537	.000
	Corr (6,2)	.715926	.005401	132.549	.000
	Corr (6,3)	.774684	.004429	174.905	.000
	Corr (6,4)	.844070	.003192	264.457	.000
	Corr (6,5)	.913667	.001827	499.987	.000
Intercept (subject = Industry*Country)	**Variance**	43.632566	6.605572	6.605	.000
Intercept (subject = Country)	**Variance**	67.473317	21.555401	3.130	.002

Dependent variable: Financial leverage