BI Norwegian Business School - campus Oslo

GRA 19502

Master Thesis

Component of continuous assessment: Thesis Master of Science

The Speed of Adjustment of Capital Structure and the Long Differencing Estimator

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Start: 02.03.2017 09.00

Finish: 01.09.2017 12.00

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Hand-in date:
31.08.2017

Examination code and name:

GRA 19502 Master Thesis

BI Norwegian Business School

Abstract

This thesis estimates the speed of adjustment (SOA) of capital structure using the long differencing estimator and finds that firms adjust back to their target leverage at a moderate pace of 20.9% per year for book leverage and 32.3% per year for market leverage. The effect of the long differencing length *k* on the SOA is examined and found to cause the long differencing estimator to overestimate the SOA when *k* is too short due to the highly persistent nature of leverage as a dependent variable. Additionally, the long differencing estimator process is tested with up to six iterations and it is determined that three are sufficient for estimation of the SOA. Finally, through a unique application of the long differencing estimator, this thesis finds that recessions, the financial crisis and coinciding great recession, and the dissolution of the American conglomerate era in the 1980s all affect firms' capital structure, albeit market leverage more than book.

Acknowledgements

We would like to sincerely thank our supervisor, Danielle Zhang Ph.D., for her timeliness, organization, insightful advice, and overall dedication to our success, it is much appreciated. We feel that her commitment and drive to push us to produce the best thesis we could is above and beyond what is expected of supervisors at BI. Consequentially, we have learned a lot of valuable skills in the process and are extremely grateful that Danielle chose to be our supervisor.

Additionally, while the long differencing estimator theory used in the regressions for our thesis is entirely by our own design based upon the works of Huang and Ritter (2009) and Hahn et al. (2007) and advice from our supervisor Danielle Zhang, Ph.D., the precise R coding was made in consultation with Patrick Herrod, B.A. DePauw University M.S. Purdue University, for his expertise in R. His professionalism, in-depth knowledge, and real-time problem solving ability proved invaluable. We would sincerely like to thank Patrick for his excellent work in helping bring our theory to life.

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1. Introduction

Estimating the speed of adjustment (SOA) of capital structure is often met with pitfalls of biases. Yet, the potential positive benefits from accurately estimating the SOA to theories of capital structure incent researchers to keep improving their techniques for its measurement. This thesis employs the long differencing estimator, the least biased technique available as demonstrated by Huang and Ritter (2009), and finds that firms adjust back to their target capital structure at a moderate pace. This finding supports the trade-off theory for determining the capital structure of firms over the long-term.

Our thesis also finds that when the long differencing length *k* is too short it overestimates the SOA because the long differencing estimator fails to sufficiently reduce the bias caused by the highly persistent nature of leverage as a dependent variable. Additionally, this thesis confirms that it is unnecessary to go beyond three iterations of the long differencing estimator process when estimating the SOA. Finally, through a unique application of the long differencing estimator, this thesis finds that recessions, the financial crisis and coinciding great recession, and the dissolution of the American conglomerate era in the 1980s all affect firms' capital structure, albeit market leverage more than book.

The overarching research of our thesis has two principal aims. The first is to estimate the SOA using the long differencing estimator and investigate how the SOA estimates react to varying the length of the long difference *k* and to the number of iterations used in its two stage least squares (2SLS) process. Given the inherent assumption of target capital structure, estimating the SOA is useful for testing the validity of the trade-off theory, which has largely been its current role in corporate finance. However, if SOA could be accurately estimated, then the field could progress to researching the applications of SOA as a metric to other aspects of finance.

Unfortunately, current research is still debating on how to accurately estimate the SOA. There is far from a consensus in the literature on SOA due to the difficulty in predicting target leverage, the short time dimension bias, and the large econometric biases between the partial-adjustment models. Since the SOA is derived from an estimated coefficient, any biasness will result in an inaccurate SOA. At present, the best that has been done is to determine the bounds between which the true SOA may lie. Estimating the SOA in our thesis will bring more clarity to the issue, provide insight into the trade-off theory of capital structure, and help the field move beyond simply trying to measure SOA to actually examining the SOA's usefulness as a metric in finance.

The second principal aim is to test the effect of economic recessions, the great recession, and the dissolution of the American conglomerate era on capital structure by employing the long differencing estimator. Significant economic events such as these can have a major impact on financial markets, and consequently the capital structure of firms. For instance, the financial crisis that resulted in the great recession of the late 2000s caused firms to reduce security issuances and financial institutions to reduce lending. Firms then increased the proportion of debt in their capital structures in reaction to the disturbance in the capital and lending markets (Fosberg, 2012). While the effect of economic events on capital structure has been examined before, approaching the question from the perspective of the long differencing estimator adds a unique angle to the existing literature.

To achieve the two aforementioned principal aims, our thesis has five hypotheses. The first is that the SOA estimated from the long differencing estimator is less biased than those produced by other estimators, and thus lies between the upper and lower SOA ranges set by models with firm fixed effects and those that ignore firm fixed effects. Using a long differencing estimator technique based upon the works of Huang and Ritter (2009) and Hahn et al. (2007), we estimate the SOA across all firms assuming homogeneity and compare it to previous SOA estimations done by Huang and Ritter (2009), Flannery and Rangan (2006), Fama and French (2002), Kayhan and Titman (2007), and Antoniou, Guney, and Paudyal (2008). Our findings are in agreement with Huang and Ritter (2009) and existing evidence that estimators which cannot reduce the bias from firm fixed effects overestimate the SOA and estimators which cannot reduce the bias due to ignoring firm fixed effects underestimate the SOA.

Our second hypothesis is that firms do have a target leverage and over the long-term the trade-off theory predominantly explains the capital structure of firms. Estimating the SOA tests the hypothesis of a target leverage because it inherently requires predicting the target leverage firms are adjusting back towards. Our highly statistically significant SOAs for every long differencing estimator regression support this hypothesis.

When Huang and Ritter (2009) estimate the SOA using the long differencing estimator they vary the length of the long difference *k*. However, they also vary the data set of sample firms they use for each length *k*. Consequently, when their estimations of SOA vary depending on *k* they explain this by stating the sensitivity of the estimates to the differencing length is partly because different firms are examined (Huang and Ritter, 2009). Our third hypothesis is that even with the same sample set of firms, the long differencing estimator will produce different SOAs for different long difference lengths *k*. This is tested by estimating SOAs with varying long difference lengths *k* on the same data set of sample firms. We find that the SOA does vary depending on the long difference *k* due to the highly persistent nature of leverage as the dependent variable causing the long differencing estimator to overestimate the SOA when *k* is not long enough.

Hahn et al. (2007) suggest that three iterations of the long differencing estimator process are often sufficient. Our fourth hypothesis is that increasing the number of iterations will improve the SOA estimates of the long differencing estimator. We run the long differencing estimator using up to six iterations on the same sample set of firms with the same long difference *k*, thereby ensuring any difference in the estimated SOAs would be due to the number of iterations. Our hypothesis proved to be incorrect, thus confirming that three iterations are sufficient for estimating the SOA. Moreover, three iterations are likely sufficient for future applications of the long differencing estimator such as those suggested by Huang and Ritter (2009): how much earnings firms pay out to shareholders, how quickly firms adjust toward a long-term target payout ratio, and why firms smooth dividends.

Our fifth and final hypothesis is that economic recessions, the great recession, and the dissolution of the American conglomerate era of the 1980s all have significant effects on the capital structure of firms. We test this by examining the dummy variables' (of the aforementioned economic events) effects on the long differenced firm leverages that serve as the dependent variable of the long differencing estimator. We find that recessions, the great recession, and the shift from internal financing and conglomerates to external financing through capital markets in the 1980s all affect firms' capital structure, albeit market leverage more than book leverage.

In short, our thesis contributes to the literature through the following ways: It brings more clarity to the upper and lower bounds of the SOA, and, in conjunction, provides more insight into the validity of the trade-off theory of capital structure. Additionally, it examines the effect of the differencing length *k* on the SOA, and if increasing the number of iterations in the long differencing estimator process improves its results. Finally, it contributes to the study of how significant economic events affect capital structure by uniquely examining them through the long differencing estimator.

The remainder of our thesis is structured as follows: Section 2 presents a literature review. Section 3 describes the data and summary statistics. Section 4 explains the methodology. Section 5 presents our results and analysis. Section 6 provides further research. Finally, Section 7 states our conclusion.

2. Literature Review

2.1 Modigliani and Miller Theorem

The Modigliani and Miller Theorem (1958) preceded the development of the theories of capital structure i.e. trade-off, pecking order and market timing theories. As noted by Frank and Goyal (2007), "before them (Modigliani and Miller), there was no generally accepted theory of capital structure." Modigliani and Miller's (1958) study focused on the irrelevance of capital structure.

Modigliani and Miller (1958) started with the assumption of a firm having a set of expected cash flows. When the firm decides on the proportion of debt and equity that it will use to finance itself, all it does is divide up the cash flows among investors. In this framework, investors and firms are assumed to have equal access to financial markets, which allows for homemade leverage. By this assumption, the investor can create any leverage that was wanted but not offered, or the investor can get rid of any leverage that the firm took on but was not wanted. As a result, the leverage of the firm has no effect on the market value of the firm (Frank and Goyal, 2007).

At the time, Modigliani and Miller (1958) stimulated a lot of interest within the topic, with many researchers setting out to disprove their theory. Ultimately, via this research, it was seen that the Modigliani and Miller theorem fails under a variety of circumstances. The most commonly referenced include: consideration of taxes, transaction costs, bankruptcy costs, agency conflicts, adverse selection, lack of separability between financing and operations, time-varying financial market opportunities, and investor clientele effects (Frank and Goyal, 2007).

2.2 The Trade-off Theory

The trade-off theory is an offshoot of the previous model presented by Modigliani and Miller (1958). As was put forward by Myers (1984), a firm's optimal debt ratio is determined by the trade-off of the costs and benefits of borrowing, holding the firm's assets and investment plans constant. Firms in this structure are balancing the value of interest tax shields against bankruptcy costs (Myers, 1984). Incorporating corporate tax into the original irrelevance proposition, a benefit for debt was seen because it shielded earnings from taxes. Given that the firm's objective is linear i.e. the more debt it takes on the more earnings are shielded, this implies that firms should be 100% debt-financed, given the lack of a counterbalancing cost of debt. It is for this reason that the cost of bankruptcy is used in this framework (Frank and Goyal, 2007).

The theory of optimal leverage reflects a trade-off between the tax benefits of debt and the deadweight costs of bankruptcy (Kraus and Litzenberger, 1973). Myers (1984) also added that a firm that follows the trade-off theory sets a target debt-to-value ratio and then gradually moves towards the target. The target is determined by balancing debt tax shields against costs of bankruptcy (Frank and Goyal, 2007). This forms the basis of the trade-off theory.

2.3 Pecking Order Theory

Fama and French (2002) assert this theory, developed or revised to some extent by Myers (1984), arises if the cost of issuing new securities overwhelm the costs and benefits of dividends and debt. The pecking order theory states that when a company needs to finance itself it should first look internally and do so via retained earnings. If this source of financing is unavailable, debt should then be utilized to satisfy its financing needs. The issuing of equity for the purpose of financing the company should be the last option.

The financing costs that produce behavior supportive of pecking order theory include the transaction costs associated with new issues. In addition, the costs that arise due to information asymmetry must be considered because of management's superior information about the firm's prospects, i.e. positive NPV projects in the pipeline, and equally important, the value of its risky security. These reasons, according to Fama and French (2002), result in the financing of new investments by firms "first with retained earnings, then with safe debt, then with risky debt, and finally, under duress, with equity."

The intuition behind this "pecking order" to methods of financing projects is in part due to what signals each source of financing sends to the market. If the company is funding itself, the signal is that it has the cash to do so and believes the project is a NPV positive one. This is a signal of financial health. Funding using debt infers that the management of the company and the market is comfortable that the company will be able to service the subsequent debt payments. Use of equity could be potentially viewed as a negative, as it might give the appearance of the company cashing in on stock they might view as overvalued.

2.4 Market Timing Theory

Market timing theory asserts that management issues securities depending on the time-varying relative costs of debt and equity and the issuance of these securities having long-lasting effects on capital structure (Huang and Ritter, 2009). According to two of its main proponents, Baker and Wurgler (2002), "capital structure is the cumulative outcome of past attempts to time the equity markets." Baker and Wurgler (2002) investigate whether equity timing affects capital structure and ultimately if there is a short-run or long-run impact.

Their results indicate that market timing has large, persistent effects on capital structure. More importantly, they conclude that low leverage firms are those that raise funds for investment in projects when their market valuations are high. Conversely, high leverage firms are those that raise funds when their market valuations are low (Baker and Wurgler, 2002).

These results are not without its critics. Alti (2006) argues that even though Baker and Wurgler (2002) find persistent effects on leverage that extend beyond 10 years, one can critique their market timing measure. The proxy for long-term growth traits of firms is a history of concurrent increases in external funding needs and market-to-book ratios. Contemporaneous control variables are noisy proxies and likely result in a spurious relationship between history and capital structure. Hovakimian (2006) finds contradictory results, finding no long-term effects for past equity market timing on market-to-book ratios.

2.5 Speed of Adjustment and the Trade-off Theory

Under the trade-off theory, management seeks to maintain a target leverage because imperfections in the market mean the capital structure of a firm affects its value (Flannery and Rangan, 2006). Various factors can push a firm from its target leverage. The rate at which the firm adjusts back to its target leverage is known as the speed of adjustment (SOA). According to Graham and Leary (2011), this deviation from target leverage is a reason traditional trade-off models often produce little explanatory power. Therefore, SOA offers a way to test the validity of the trade-off theory by considering these deviations.

SOA assumes that there is an actual target leverage, in contrast to theories such as market timing and pecking order. Huang and Ritter (2009) believe that SOA is perhaps the most important issue in capital structure research today. If firms actively adjust back to a target leverage over time, then capital structure decisions based on market timing or pecking order should only have short-term effects. Mean reversion to a target leverage would not exist for either market timing or pecking order. SOA therefore supports trade-off theory as the predominant force behind a firm’s capital structure decisions over market timing and other theories that do not assume target leverage (Flannery and Rangan, 2006). Although, it is important to note that some researchers do not believe that mean reversion alone adequately proves firms seek a target capital structure (Graham and Leary, 2011).

2.5.1 Existing Work on the Speed of Adjustment

Many of the past studies on SOA use a partial-adjustment model to estimate the average SOA for firms as a whole. This method inherently assumes the average SOA is the same across all firms (Elsas and Florysiak, 2011). Under this method much of the research primarily supports the trade-off theory by concluding that firms do have targets (Faulkender et al., 2012). However, evidence for market timing and pecking order is not completely absent. Huang and Ritter (2009) state that their estimates of the SOA toward target debt ratios suggest that firms do move toward target debt ratios, but their results imply that market timing and pecking order also contribute to the capital structure of firms.

Flannery and Rangan (2006) find support for market timing and pecking order as well, although it is minimal in comparison to the support they find for trade-off theory. Targeting behavior displayed by firms account for over 50% of their capital structure changes compared to not even 10% for market timing and pecking order. The evidence that firms actively seek target leverage is strong for various firm sizes, time periods, and for book and market-valued leverage ratios. Market timing and pecking order are statistically significant in Flannery and Rangan (2006), but have their effect overwhelmed by firms' efforts to obtain a target leverage.

However, as noted by Frank and Goyal (2009), while corporate leverage is largely agreed upon by the literature to be mean reverting at the firm level, the SOA to the target is by no means a settled issue. Graham and Leary (2011) agree that despite the amount of existing research, the rate of mean reversion is still an open question. They feel that the current body of SOA studies is not strong enough to say that firms actively manage toward a target leverage. Reasons for this are the mismeasurement of the SOAs and the biasness of the partial-adjustment models used. *Table 1* (See Appendix A) displays the SOAs from some of the more notable studies. For book leverage the SOA ranges from 10% by Fama and French (2002) with a half-life of 6.6 years, to 34.2 % by Flannery and Rangan (2006) with a half-life of 1.7 years.

For market leverage Fama and French (2002) again have the slowest SOA at 7% with a half-life of 9.6 years compared to Flannery and Rangan's (2006) SOA of 35.5% and half-life of 1.6 years. Eight years is a massive difference in the length of time it would take a firm to remove half of the effect of a shock on its leverage. Indeed, as Graham and Leary (2011) point out, the issue of biases in the measurement of adjustment speeds is a significant problem and one of the contributing factors to the wide range of SOAs.

[See Table 1 in Appendix A]

Under reasonable assumptions an OLS estimated coefficient of the partial-adjustment model, as used by Fama and French (2002) and Kayhan and Titman (2007), that ignores firm fixed effects is biased upwards, meaning it will underestimate the SOA (Huang and Ritter 2009). It is no coincidence, therefore, that Fama and French (2002) have the slowest SOA. Some researchers believe that one reason for mismeasurement in SOA is ignoring firm fixed effects because the regular determinants for target leverage are producing unexplained variations. However, adding firm fixed effects makes consistently estimating the SOA difficult due to their presence in the error (Graham and Leary, 2011). Mean differencing estimators with firm fixed effects and system generalized method of moments (GMM) estimators with firm fixed effects are biased downwards, meaning they will overestimate the SOA (Huang and Ritter, 2009). Consequently, Flannery and Rangan (2006) have the highest SOA using a fixed effects estimator. Fortunately, the opposite biases of the OLS and fixed effects estimators allow the SOA to be approximately bounded and a range established (Graham and Leary, 2011).

In an attempt to reduce the bias, Huang and Ritter (2009) employ a new econometric technique known as a long differencing estimator. This technique was first proposed by Hahn et al. (2007) and theoretically helps reduce the bias caused when the dependent variable is highly persistent, such as with leverage ratios. Huang and Ritter (2009) state that estimates using the long differencing method are less biased than the OLS estimator that ignores fixed effects except in the case the true SOA is very slow; however, in this scenario neither method would have much bias. Likewise, the long difference estimator is less biased than the firm fixed effects estimators except when the true SOA is very fast, although in this case neither estimator would have much bias. With the long differencing technique Huang and Ritter (2009) find an SOA of 17.0% for book leverage with a half-life of 3.7 years and a SOA of 23.2% for market leverage with a half-life of 2.6 years.

All of the models mentioned so far are partial-adjustment models, which have come under criticism for biased estimates of coefficients and for a poor ability to differentiate leverage targeting from other financial motives (Graham and Leary 2011, Shyam-Sunder & Myers 1999, Chang & Dasgupta 2009). A dynamic panel data with a fractional dependent variable estimator (DPF) as proposed by Elsas and Florysiak (2010) takes a different approach than partial-adjustment models. While partial-adjustment models assume homogeneity in the SOA across all firms, the DPF estimator allows for heterogeneity across the SOA for firms.

Elsas and Florysiak (2011) argue that given adjustment costs are often specific to firms and investments, the speed of adjustment is also often not homogeneous. The DPF estimator proposed by Elsas and Florysiak (2010) is constructed to be unbiased with unbalanced dynamic panel data. Elsas and Florysiak (2011) go on to run simulations that corroborate their claim that it is unbiased. There have not been many studies allowing for heterogeneity in SOA, with Faulkender et al. (2012) being one of the more notable. However, Elsas and Florysiak (2011) address more heterogeneous characteristics with their model than Faulkender et al. (2012). The SOAs estimated by Elsas and Florysiak (2011) vary, with some being as high as 60%.

2.6 Our Contribution to the Literature

Our thesis contributes to the literature in the following ways: It brings more clarity to the upper and lower bounds of the SOA, and, in conjunction, provides more insight into the validity of the trade-off theory of capital structure. Additionally, it examines the effect of the differencing length k on the SOA, and if increasing the number of iterations in the long differencing estimator process improves its results. Finally, it contributes to the study of how significant economic events affect capital structure by uniquely examining them through the long differencing estimator.

3. Data and Summary Statistics

3.1 Data

The unbalanced panel data consists of annual North American firm data from 1961 to 2016. All firm-level data are from Compustat and the Center for Research in Security

Prices (CRSP) databases. Regulated enterprises (SIC 4900-4999) and financial services (SIC 6000-6999) are not included in the sample because their capital decisions may reflect special factors (Flannery and Rangan, 2006). Firms with format codes 4 and 6 are excluded because they are not defined in Compustat and firms with format code 5 are also excluded because they are Canadian. To mitigate the effect of outliers, firms with book assets currently valued at less than 10 million, firms with a book or market leverage greater than one or negative, and firms with a Tobin's Q greater than ten or negative are all excluded. The No. 94 Statement of Financial Accounting Standards (SFAS) accounting change which required firms to consolidate off-balance sheet financing resulted in many heavy equipment manufacturers and retailers vastly increasing their debt. Therefore, firm-year observations that included No. 94 SFAS are excluded (Huang and Ritter, 2009). The largest final data set used in this study only includes firms with a minimum of 7 years of consecutive data and consists of 63,187 firm-year observations. As the dataset used for the shortest long difference of k = 4 years, it encompasses all of the firms used by the smaller datasets of k = 8, 10, and 12.

The book debt used in calculating the leverage ratios is defined as total liabilities plus preferred stock (item 10) minus deferred taxes (item 35) and convertible debt (item 79), as done by Fama and French (2002) and Baker and Wurgler (2002). If the liquidating value of preferred stock (item 10) is unavailable, then the redemption value (item 56) is used. Should this also be missing the carrying value (item 130) is used. 51% of the firm years in the original data have missing R&D. These missing values are converted to zero to avoid losing a significant amount of observations. Industries where R&D is likely to be zero, such as clothing retailers, account for a large portion of the missing values. A dummy variable is used to capture the effect of the missing R&D firm years (Huang and Ritter, 2009). Some capital expenditures and convertible debt firm-years are missing. As with R&D, these missing values are replaced with zero.

Price Close – Annual – Fiscal (item 199) is used in the calculation of the market leverage and Q variables. When this is unavailable, the Price Close – Annual – Calendar (item 24) is used. If this is missing as well, then the Price Close – Monthly – December (item 12) from CRSP is used. Finally, if this is also unavailable the Price Close – Quarterly – Fiscal – 4th Quarter (item 14) is used.

The implied equity risk premium (ERP) data comes from Aswath Damodaran's website, who is a Professor of Finance at New York University Stern School of Business. Data used to create the real interest rate (RIR), default spread (DSP), term spread (TSP), and real gross domestic product (RGDP) is from the Federal Reserve Bank of St. Louis. The statutory corporate tax rate data (TAXR) is from the World Tax Database, Office of Tax Policy Research. Recession data for the economic recession dummy variable (ERD), years 1970, 1974, 1975, 1980, 1981, 1982, 1990, 2001, 2008, 2009, and the great economic recession dummy variable (GERD), years 2008 and 2009, is from the CATO Institute (Hummel, 2015). Years are designated recession years if at least six months of the year was in a period of recession. The conglomerate dummy variable years, 1980 – 1989, are taken based on the work of Davis, Diekmann & Tinsley (1994).

3.2 Summary Statistics

Table 2 (See Appendix A) presents the summary statistics for companies with at least 7 consecutive years of data from 1961 – 2016. As the dataset used for the shortest long difference of k = 4 years, it encompasses all of the firms used by the smaller datasets of k = 8, 10, and 12. The summary statistics are done for all variables to be used in the regressions (BL, ML, Q, R&D, CAPEX, SALE, OIBD, TANG, ERP, RIR, DSP, TSP, TAXR, RGDP) resulting in 63,187 observations.

[See Table 2 in Appendix A]

These variables are included in the long differencing estimator as done by Huang and Ritter (2009). Chief importance amongst these variables are the dependent variables for the regressions. The book leverage (BL) has a mean of 44.3% and a median of 45.2%, indicating that the values for BL are only very slightly skewed to the left. This proximity between the two values is confirmed by the skewness value being approximately 0. The market leverage (ML) has a mean of 38.9% and a median of 37.7%. This again indicates the values are slightly skewed, this time to the right, with a skewness value of 0.25. Comparison of the book and market leverages shows that in addition to the book leverage being higher, it is also less volatile with a standard deviation of 18.8% compared to 22.6% for market leverage.

4. Methodology

4.1 Estimating the Speed of Adjustment

The long differencing estimator first proposed by Hahn et al. (2007) and first used to measure SOA by Huang and Ritter (2009) is the econometric technique chosen for this study because it is the least biased of all the available techniques used to measure SOA.

System GMM and mean differencing estimators which include firm fixed effects are biased in overestimating the SOA while OLS estimators which ignore firm fixed effects are biased in underestimating the SOA. The difference between these two estimates is large, and exacerbated by the short time dimension bias. Huang and Ritter (2009) show that when only using firms with five consecutive years of data the difference between the firm fixed effects and mean differencing estimator measurement of SOA is 58.2% for book leverage and 62.9% for market leverage. Whereas when only using firms with thirty consecutive years of data there is merely a 10.4% difference in the SOA of book leverage and 13.6% for market leverage. Reducing the short time dimension bias substantially shrinks the range between the over- and underestimations of the SOA by those techniques that include firm fixed effects and those that do not.

Early attempts at overcoming the short time dimension bias relied on GMM and first difference estimators, such as those done by Arellano and Bond (1991) and Anderson and Hsiao (1981). Lagged values of predetermined or endogenous variables are used as instruments in these estimators for the first differences. In turn, these first differences get rid of the unobserved firm-specific effects. Unfortunately, these estimators fall short when faced with highly persistent data due to their large finite sample biases when the autoregressive parameter is close to one (Huang and Ritter, 2009). As leverage ratios are highly persistent, these estimators are unreliable for the dataset being used in this thesis.

An extended, or system, GMM estimator as proposed by Arellano and Bover (1995) and employed by Antoniou et al. (2008) and Lemmon et al. (2008) handles persistent data better than first differencing estimators by imposing additional moment restrictions (Blundell and Bond, 1998). However, as the time dimension becomes large finite sample bias becomes an issue for system GMM estimators, such as overfitting the endogenous variables with a large number of instruments (Huang and Ritter, 2009). In comparison, the long differencing estimator relies on a less than full set of moment conditions and does not have the same issues with weak instruments.

Overall, the long differencing estimator has substantially less bias. Hahn et al. (2007) provide a numerical example of its reduced bias compared to that of the system GMM estimators. In a given simulation the true autoregressive parameter is 0.9. Using a differencing length of $k = 5$ the long differencing estimator produces a remarkably accurate estimate of 0.902. In contrast, the system GMM estimate is 0.664. Through their own numerical simulations, Huang and Ritter (2009) show that even in situations that plague other estimators, such as when the autoregressive parameter is close to one, the long differencing estimator still functions properly.

4.2 The Long Differencing Estimator

According to Hahn et al. (2007), who first proposed it, the long differencing estimator is a, "…new instrumental variables estimator for a dynamic panel data model with fixed effects with good bias and mean squared error properties even when identification of the model becomes weak near the unit circle."

As the name suggests, the long differencing estimator takes "long differences" of length k instead of only "first differences" as in other estimators. The base long differencing estimator equation is the result of the subtraction of two equations. The first comes from the dynamic panel model with firm fixed effects. In this model it is assumed that both observed and unobserved firm characteristics dictate target capital structure. The unobserved characteristics are captured by the firm fixed effects. The following equations compose the dynamic panel model with firm fixed effects:

(1) $L_{it} - L_{it-1} = \gamma(TL_{it} - L_{it-1}) + \tilde{\varepsilon}_{it}$

And

(2) $TL_{it} = \alpha_i + \beta X_{it-1}$

L_{it} is the leverage ratio for firm i at the end of year t while TL_{it} is the target leverage of firm i at the end of year t. Firm fixed effects are captured by α_i and X_{it-1} represents lagged firm characteristics of firm i, lagged or current macroeconomic indicators, and dummy variables. The SOA is measured by γ. If TL_{it} was readily known then the estimation of equation (1) would be straightforward to find the SOA. However, TL_{it} is unobservable, which means it has to be predicted using information that is observable. Therefore, the equation used in practice is the following:

(3) $L_{it} = (1-\gamma)L_{it-1} + \gamma\alpha_i + \gamma\beta X_{it-1} + \tilde{\varepsilon}_{it}$

This is the first of the two equations subtracted to get the long differencing estimator. The second being the equation that determines the leverage in year $t-k$:

(4) $L_{it-k} = (1-\gamma)L_{it-k-1} + \gamma\alpha_i + \gamma\beta X_{it-k-1} + \tilde{\varepsilon}_{it-k}$

Subtracting equation (4) from equation (3) yields the long differencing estimator base equation:

(5) $L_{it} - L_{it-k} = (1-\gamma)(L_{it-1} - L_{it-k-1}) + \gamma\beta(X_{it-1} - X_{it-k-1}) + \tilde{\varepsilon}_{it} - \tilde{\varepsilon}_{it-k}$

Or

(6) $\Delta L_{it,t-k} = \lambda\Delta L_{it-1,t-k-1} + \delta\Delta X_{it-1,t-k-1} + \tilde{u}_{it,t-k}$

The long differencing estimator comprises an iterated two-stage least squares (2SLS) estimation of equation (6) (Huang and Ritter, 2009). The iterated 2SLS is necessary to improve the valid instruments used to create the long difference of the leverage variable $\Delta L_{it-1,t-k-1}$ used in the base equation. For a thorough explanation of the full long differencing estimator process (See Appendix B).

4.3 Dummy Variables

There are two economic recession dummy variables used in this thesis. The first is an economic recession dummy (ERD) that is used to capture the years during the time series where the United States was experiencing an economic recession: 1970, 1974, 1975, 1980, 1981, 1982, 1990, 2001, 2008, 2009 (Hummel, 2015). The second dummy variable is the great economic recession dummy (GERD). This dummy variable is used as a marker for the recession during years 2008 and 2009. The choice to give this a separate dummy variable is driven by the significance of the last recession. There have been several studies, such as Duggal and Budden (2011) and Fosberg (2012), focusing specifically on the impact of the great recession on capital structure. However, our thesis approaches the question through implementing the long differencing estimator. The dependent variable in the long differencing estimator, $\Delta L_{it,t-k}$, is the long difference between two leverages for a given firm *i* and given years *t* and *t-k*. This study aims to provide further insight into the great recession's effect on capital structure through examining its effect on this long difference between leverages.

Shleifer and Vishny (1992) state in their paper that a firm's debt capacity depends on current economic conditions. This is supported by D. Hackbarth et al. (2006), who state that macroeconomic conditions should have a large impact not only on credit risk but a firm's financing decisions. Furthermore, when the firm can adjust its capital structure dynamically, both the pace and the size of the adjustments depend on current economic conditions. They go on to conclude that firms should adjust their capital structure more often and by smaller amounts in booms than in recessions (D. Hackbarth et al., 2006).

In 1980, the conglomerate was the dominant corporate form in the United States. However, this was not the case at the end of the following decade. By the end of 1990, this corporate form had in effect become deinstitutionalized (Davis, Diekmann & Tinsley, 1994). The period 1980 – 1989 captures an important time particularly relevant to this study. As conglomerates dissolved, so too are sources of internal financing for some companies. The run-off effect is that these smaller, more streamlined companies would now have to approach public sources of capital. It is with this intuition that the conglomerate dummy is also included in this study. The goal of this dummy variable is to capture this expected change in leverage during the aforementioned period by examining the long differences of firms' leverages.

5. Results

5.1 Speed of Adjustment's Support for the Trade-Off Theory

The long differencing estimator regressions which compose *Table 3* (See Appendix A) are run to test our hypothesis that firms do have a target leverage and over the long-term the trade-off theory predominantly explains the capital structure of firms. Additionally, varying the differencing length *k* and consequently the sample set of firms used is the same methodology from Huang and Ritter (2009) and thus allows the direct comparison of results.[1]

[1]As the differencing length increases the minimum number of years per firm required to run the long differencing estimator increases as well.

Huang and Ritter (2009) try differencing lengths of k = 4, 8, 18, and 28; however, they only discuss the SOA estimated with k = 8 in their conclusion suggesting that they believe a differencing length of 8 produces their best results. Therefore, the differencing lengths chosen for the long differencing estimator (specification (6) in methodology) of k = 4, 8, 10, and 12 reside close to Huang and Ritter's (2009) favored differencing length of 8. The datasets for specification (6) only include firms with a minimum of 7, 11, 13, and 15 years of consecutive data respectively. *Table 3* summarizes the estimated coefficients and t-statistics for book and market leverage. The estimated SOA is found by taking the estimated coefficient of $\Delta L_{it-1,t-k-1}$ and subtracting it from 1.

[See Table 3 in Appendix A]

In Panel A and B, the estimated SOA for book leverage is between 19.1% and 39.7% per year and between 28.4% and 48.5% for market leverage depending on the differencing length. For the differencing length of k = 4 years, the estimated SOA for book leverage is found to be 39.7% and 48.5% for market leverage. Huang and Ritter (2009) estimate these to be 21.1% for book leverage and 22.3% for market leverage. For differencing length of k = 8 years, this study finds SOA for book leverage to be 24.4% and 34.9% for market leverage. Huang and Ritter (2009) estimate these to be 17.0% for book leverage and 23.2% for market leverage.

Direct comparison of the results of this thesis and that of Huang and Ritter (2009) shows that in this study, the SOA estimated is faster for both book and market leverages. This might in part be due to the fact that different datasets are used. Also, the inclusion of the period of the great recession might be playing a role in faster estimates of SOA. Overall, what is most important are the trends observed in both studies. Most notable of these trends is the recurring pattern of market leverage SOA being consistently faster than book leverage SOA.[2]

[2]It is noted by Huang and Ritter (2009) that, intuitively, this result is a strange one. Especially in light of Welch (2004) demonstrating that firms do not actively offset increases in market value of equity caused by stock price increases. Huang and Ritter (2009) speculate that in the event of a firm sharply increasing their market debt ratios due to a stock price decrease, it is likely that the stock price either recovers and remains in sample or drops out of the sample altogether due to financial distress or acquisition by another company. This resulting selection bias would create the bias towards estimating a faster SOA with market leverages compared to book.

In all cases shown in *Table 3*, i.e. varying differencing length and minimum number of years, this thesis observes very strongly significant SOAs. This lends credence to the trade-off theory, specifically that companies do have a target debt ratio. Frank and Goyal (2009) note that corporate leverage is mean reverting at the firm level. This mean reversion does lend strong support to the trade-off theory, but on its own does not give conclusive evidence. Noted skeptics of whether the presence of mean reversion in debt ratios is evidence of a target ratio include Chang and Dasgupta (2009) and Chen and Zhao (2007) who question the use of the estimation of SOA as evidence. They suggest that the estimation of SOA could likely be a manifestation of a mechanical relation if firms are financing randomly or semi-randomly. Huang and Ritter (2009) refute this, showing in their study that firms are not financing randomly.

5.2 Speed of Adjustment and the Length of the Long Difference *k*

To test our hypothesis that even with the same sample set of firms the long differencing estimator will produce different SOAs for different long difference lengths *k*, *Table 4* (See Appendix A), unlike *Table 3*, only uses the long differencing estimator (specification (6) in methodology) on a sample set of firms with at least 20 years of continuous data no matter what the long difference *k* is. Huang and Ritter (2009) state in their results that the sensitivity of the estimates to different lengths of *k* is partly because different firms are examined. By ensuring that the firms used by the long differencing estimator are the same for all *k* lengths, *Table 4* isolates the effect of purely increasing lengths of *k* on the SOA. In addition, Huang and Ritter (2009) point out that the long differencing estimator is not as sensitive to the short time dimension bias as other estimators. However, it is still not immune, and requiring all firms to have at least 20 years of continuous data helps mitigate any remaining bias from too short of a time dimension. *Table 4* displays the estimated coefficients and t-statistics for book and market leverage. The estimated SOA is found by taking the estimated coefficient of $\Delta L_{it-1,t-k-1}$ and subtracting it from 1.

[See Table 4 in Appendix A]

The SOA is highly statistically significant for both book and market leverage and for all lengths of *k*. For book leverage the SOA ranges from 38.4% with $k = 4$ to 18.9% with $k = 12$. As with *Table 3* the market leverages are faster, with a SOA ranging from

47.8% with *k* = 4 to 27.7% with *k* = 12. Overall, the results from *Table 4* are almost identical to those of *Table 3* except for each respective length of *k* having a slightly slower SOA and slightly higher Adj. R^2.

Despite controlling for the sample firms used by the long differencing estimator, the SOA still varies depending on *k*. As can be seen in *Figure 1* (See Appendix A), the biggest jump is between *k* = 4 to *k* = 8 with book leverage dropping from a SOA of 38.4% to 23.5%, and market leverage from 47.8% to 33.9%. In comparison, from *k* = 8 to *k* = 12 book leverage SOA only drops from 23.5% to 18.9% while market leverage drops from 33.9% to 27.7%. The same pattern is seen in the Adj. R^2. Overall, the negative relationship between the SOA and length of *k* forms a roughly convex downward graph.

[See Figure 1 in Appendix A]

The rapid decrease in SOA from *k* = 4 to *k* = 8 followed by a tapering off in SOA from *k* = 8 to *k* = 12 can be explained by the highly persistent nature of leverage as a dependent variable. Previous methods for estimating the SOA such as OLS ignoring firm fixed effects, mean differencing estimator with firm fixed effects, and system GMM with firm fixed effects are biased when leverage is highly persistent. Estimators that include firm fixed effects are biased downwards meaning they overestimate the SOA.[3] The long differencing estimator also includes firm fixed effects, but is supposed to reduce the bias caused by a highly persistent dependent variable by employing long differences (Huang and Ritter, 2009).

However, a *k* length of 4 appears not to be a long enough difference to mitigate the bias from the highly persistent leverage. Since the long differencing estimator includes firm fixed effects, this bias shows up in the form of an overestimated SOA. Once *k* = 8, this bias has been significantly reduced by the long differences, making the SOA much more consistent as *k* increases. In conclusion, the reason for the roughly convex relationship between SOA and the length of *k* in the long differencing estimator is the result of *k* needing to reach a certain threshold length before the differences are

[3] Recall that SOA is $1 - \Delta L_{it-1,t-k-1}$ coefficient.

sufficiently long enough to mitigate the downward bias from the firm fixed effects in conjunction with the highly persistent leverage.

5.3 The Effect of Major Economic Events on Capital Structure

Dummy variables are used in the long differencing estimator (specification (6) in methodology) to test our hypothesis that economic recessions, the great recession, and the dissolution of the American conglomerate era of the 1980s all have significant effects on the capital structure of firms. By using the same dataset for all long difference lengths of *k*, that only includes firms with at least 20 years of consecutive data, *Table 4* (See Appendix A) allows a clearer look at the dummy variables GERD (great economic recession dummy), ERD (economic recession dummy), and CONGD (conglomerate dummy). *Table 4* displays the estimated coefficients and t-statistics for book and market leverage.

[See Table 4 in Appendix A]

5.3.1 Great Economic Recession

For book leverage GERD is statistically significant at the 0.1% level for all lengths of *k*, ranging from 1.5% for k = 10 to 4.1% for k = 12. This means that the difference between a given firm's leverage during the great recession and its leverage *k* years before or after is greater than the difference in leverages had neither year been during the great recession. For example, if k = 8 the difference in a given firm's book leverage from 2000 to 2008 is 2.4% greater than the difference would have been had 2008 not been a great recession year.

For market leverage GERD is statistically significant at the 0.1% level for k = 4, 8, and 12 with coefficients of 7.2%, 6.7%, and 6.2% respectively. It is also statistically significant at the 5% level for k = 10, but unlike all of the other GERD coefficients, is negative, being -1.2%. The larger percent changes in the differences in market leverage than book may be a result of a change in the capital markets during the great recession having a greater impact on market assets than book assets. Including both book and market leverages, seven out of the eight GERD coefficients indicate the great recession has a positive effect on the difference in leverages for a given firm while one GERD coefficient indicates a negative effect. However, all GERD coefficients are in consensus in indicating the great recession had a significant effect on the capital structure of firms.

Fosberg (2012) finds that between 2006 and 2008 the financial crisis and coinciding great recession caused sample firms to increase their market to debt ratios by an average of 5.5%. Akin to our thesis, there was a smaller percentage change in book to debt ratios than market to debt. Duggal and Budden (2011) also examine the effect of the 2007 – 2009 recession on corporate leverage. As with our thesis and Fosberg (2012) they find there is a significant effect on market leverage. Duggal and Budden (2011) find stock price declines during the recession caused a significant increase in market leverage.

However, in contradiction to Fosberg (2012) and our thesis, they find no significant shift in book leverage from the great recession because they claim firms were able to offset the reduced book value of equity due to the recession-induced losses with reduced dividends and debt levels (Duggal and Budden, 2011). This difference may be due to Duggal and Budden (2011) only examining the 419 non-financial firms of the S&P 500, whereas our thesis uses a much larger dataset which encompasses firms outside the S&P 500.

5.3.2 Economic Recessions

For book leverage, ERD is statistically significant at the 5% level for $k = 4$ with a coefficient of -0.6%. Unlike GERD it is not significant for any other k. This may be due to the other recessions ERD encompasses being of less severity than the great recession. However, for market leverage ERD is statistically significant at the 1% level for $k = 4$, and at the 0.1% level for $k = 8$ and $k = 12$. Their coefficients are -1%, -3.1%, and 2.3% respectively. The larger effect of a stock market decline during a recession on market assets than book assets is a plausible reason that ERD is significant for more of the k lengths in market leverage than book leverage.

In contrast to GERD, three of the four significant ERD coefficients are negative, with only one being positive. This counterintuitive result may be because for ERD both of the differenced leverage years could be in recessions. For instance, 1970 and 1974 are both recession years and if $k = 4$ they would be differenced $\Delta L_{i1974,1970}$. Whereas, for

GERD this does not happen because the years are only 2008 and 2009. Nonetheless, the numerous statistically significant ERD coefficients support the idea that recessions have an effect on capital structure.

5.3.3 Dissolution of the American Conglomerate Era

For book leverage CONGD is not statistically significant for any length of k. Although for market leverage it is statistically significant at the 0.1% level for k = 4, 8, and 10, with coefficients of 3.3%, 3.7%, and 3.1% respectively. In contrast to k = 4, 8, and 10, the coefficient for CONGD for k = 12 is negative, although it is only statistically significant at the 10% level and is barely negative at -0.9%. Therefore, there is stronger evidence for the positive CONGD coefficient which means, for example, if k = 8 that the difference in a given firm's market leverage from 1976 to 1984 is 3.7% greater than the difference would have been had 1984 not been during the time conglomerates across America were dissolving.

This supports the idea that the shift from conglomerates and internal financing prior to the 1980s, to smaller firms accessing the public capital markets for external financing, affected firm's capital structure. The reason CONGD is never significant for the book leverage is likely due to the shift towards external financing having a more pronounced impact on market assets than book assets.

5.4 Long Differencing Estimator Iterations and the Speed of Adjustment

In *Tables 3* and *4* the results reported are from the third iteration of the long differencing estimator process (See Appendix B for details) as done by Huang and Ritter (2009) because Hahn et al. (2007) suggest that 3 iterations are often sufficient. Huang and Ritter (2009) do not report results for anything other than 3 iterations, although they may have conducted unreported analysis using greater than 3 iterations.

To test our hypothesis that increasing the number of iterations will improve the SOA estimates of the long differencing estimator, *Table 5* (See Appendix A) reports the results of the long differencing estimator (specification (6) in methodology) using 4, 5, and 6 iterations, along with the standard 3 iterations for comparison. All iterations use the same differencing length of k = 10 and a minimum of 20 years of continuous data so that any changes in the SOA are due to the number of iterations. *Table 5* displays the estimated coefficients and t-statistics for book and market leverage. The estimated SOA is found by taking the estimated coefficient of $\Delta L_{it-1,t-k-1}$ and subtracting it from 1.

[See Table 5 in Appendix A]

The 3rd iteration SOA is 20.9% for book leverage and alters back and forth between 20.9% and 20.8% for iterations 4 through 6. While the 3rd iteration SOA is 32.3% for market leverage and only decreases slightly to 32.2% for iterations 4 through 6. Changes in the SOA past 3 iterations are insignificant such that for all intents and purposes it remains exactly the same.

The main purpose of the iterations in the long differencing estimator is to improve the residuals used as valid instruments in the 2SLS process (See Appendix B). *Table 6* (See Appendix A) displays the estimated coefficients and t-statistics for the last regression run using residuals as valid instruments for each iteration. If increasing iterations did have a positive impact then it would be expected to see an improvement in the Adj. R^2 from iteration 3 to 6.

[See Table 6 in Appendix A]

However, the Adj. R^2 of 96.8% for book leverage and 93.3% for market leverage remains unchanged from iteration 3 to 6. Therefore, *Tables 5 and 6* confirm that the 3 iterations of the long differencing estimator as suggested by Hahn et al. (2007) are sufficient for estimating the SOA.

5.5 Comparison to Previous Articles' Estimations of Speed of Adjustment

To test our hypothesis that the SOA estimated from the long differencing estimator is less biased than those produced by other estimators, and thus lies between the upper and lower SOA ranges set by models with firm fixed effects and those that ignore firm fixed effects; *Table 1* (See Appendix A) displays our SOA for book and market leverage estimated using k = 10 and sample firms with a minimum of 20 years of consecutive data in comparison to other articles' estimates of SOA. *Table 1* displays both the book and market leverage SOAs in terms of percentage per year and half-life.

[See Table 1 in Appendix A]

The 20.9% SOA for book leverage estimated in this thesis is 3.9% faster than that estimated by Huang and Ritter (2009) while the 32.3% SOA for market leverage is 9.1% faster. This faster measurement of SOAs is likely a result of the different datasets used. Huang and Ritter (2009) only used a dataset with firms from 1969 – 2001 while this thesis uses a dataset with firms from 1961 – 2016. This thesis's dataset also encompasses the great recession, which has been shown to significantly affect capital structure, especially in regards to market leverage. This could help explain the greater difference in the market leverage SOAs estimated in this thesis and by Huang and Ritter (2009) compared to the book leverage SOAs.

Despite our thesis's SOA estimates being slightly faster than those of Huang and Ritter (2009), they corroborate the existing evidence that the mean differencing with firm fixed effects and system GMM with firm fixed effects are biased downwards whilst the OLS ignoring fixed effects is biased upwards. Our thesis's book leverage SOA is 10. 9% faster than both Fama and French's (2002) estimated SOA using dividend- paying firms and that of Kayhan and Titman (2007). It is also 2.9 % faster than Fama and French's (2002) SOA using non-dividend paying firms. The difference is even more pronounced when comparing the market leverage SOAs from these articles . This provides further evidence the OLS ignoring firm fixed effects employed by these articles underestimates the SOA.

Furthermore, this thesis's book leverage SOA is 13.3% slower than that of Flannery and Rangan (2006) and 4.1% slower than that of Lemmon, Roberts, and Zender (2008). The market leverage SOA is 3.2% slower than that of Flannery and Rangan (2006) while being merely 0.1% faster than Antoniou, Guney, and Paudyal (2008). Antoniou, Guney, and Paudyal (2008) being fractionally faster may be due to this thesis's dataset including more recent years. Nonetheless, altogether our thesis's findings support the idea that mean differencing estimators with firm fixed effects and system GMM estimators with firm fixed effects overestimate the SOA.

6. Further Research

As seen in preceding sections, the SOA of a firm's capital structure is a useful metric to gauge how far the firm is from its target leverage and how fast it is adjusting towards it. Whilst this knowledge is useful, the existing body of work in the field has yet to tackle exactly how the SOA can be utilized. One possible way in which the SOA can be utilized is to examine its relationship with a firm's performance.

A company that is more efficient and better run with healthy positive cash flows has a greater ability to adjust their capital structure to the desired level in the aftermath of deviations due to internal and external factors. Intuitively, leverage targets are easier to meet if a firm has the capital and capacity to do so. Faulkender et al. (2012) conclude that firms with high absolute cash flows and high absolute leverage deviations make larger capital structure adjustments than firms with similar leverage deviations but cash flow realizations near zero. This means that adjustments of leverage are more likely to be made when costs are shared with transactions related to the firm's operating cash flows (Faulkender et al., 2012).

Adjustment in leverage costs money. Recent research has emphasized the impact of transaction costs on firm leverage adjustments. In the aforementioned 2012 study, they found that a firm's cash flow features affect not only the leverage target but also the SOA to that target (Faulkender et al., 2012).

To test the relation between SOA and firm performance, firm specific SOA could be regressed upon return on assets (ROA) as a substitute for performance. Fosu (2013) also selected ROA when testing the effect of leverage on firm performance. To avoid endogeneity SOA would be lagged in the following regression:

$$(7)\ ROA_{it} = \alpha + \beta_0 SOA_{it-1} + (control\ variables)_{it-1} + \varepsilon_{it}$$

SOA would be entered in its percentage form $(1-\lambda)$ and therefore a positive and significant $\beta_0$would indicate that a faster SOA is associated with an increase in ROA and higher firm performance. If a significant relationship is determined, the next step would be to see how many further years could the SOA have a significant relationship with ROA. For example:

$$(8)\ ROA_{it+3} = \alpha + \beta_0 SOA_{it-1} + (control\ variables)_{it-1} + \varepsilon_{it}$$

Currently, there are several significant issues preventing the testing of the relationship between SOA and ROA. First, in order to run the aforementioned regression (7) firm-specific SOA must be estimated, as compared to the overall SOA measured in this study. However, even with excluding all of the dummy variables, the long differencing estimator used in this study and by Huang and Ritter (2009) is composed of 12 independent variables, making degrees of freedom a serious problem. According to Austin and Steyerberg (2015) at least two subjects per variable (SPV) are required in multivariate linear regression models estimated with OLS to ensure accurate estimation of the standard errors and coefficients with a relative bias less than 10%. This means regression (7) could only be estimated for firms with at least 25 years of data.[4] Consequently, at a minimum the SOA estimated from the previous 24 years would be regressed upon the ROA of the current year:

$$(9)\ ROA_{it} = \alpha + \beta_0 SOA_{it-1\ to\ it-25} + (control\ variables)_{it-1} + \varepsilon_{it}$$

The resulting survivorship bias would diminish any results from regression (9) as the sample is not representative of all firms, but only those which performed well enough to survive 25 years.

In addition to the survivorship bias, there is also the inherent measurement bias in estimating the SOA with the existing techniques. The long differencing estimator is currently the least biased method, but does not eliminate the bias completely. Any bias in the estimated SOA will only be amplified when used in regression (9) as an independent variable, thereby increasing the difficulty of determining the true relationship between SOA and ROA.

To overcome the survivorship bias, a new econometric technique needs to be developed that dramatically reduces the length of time required to estimate the SOA. Using quarterly data instead of yearly data, as used in this study, would help decrease the time required to have enough degrees of freedom. However, the Compustat and CRSP databases used for this thesis did not contain all of the necessary quarterly data to run the long differencing estimator. Therefore, a new database containing all of the required

[4] One year is added because SOA is lagged

quarterly data would need to be made and continually updated for the future. Although, even if an econometric technique was able to estimate the SOA with only a few years of data, the short time dimension bias as presented by Huang and Ritter (2009) would still be a significant hurdle. Huang and Ritter (2009) made it clear that estimating the SOA with 30 years of data produced much less bias than using only 5 years of data. The new econometric technique will not only need to be able to estimate the SOA using only a relatively short period of time, but to be able to estimate it with little bias.

It is hopeful that these current problems will be overcome because the shorter the amount of time required to accurately estimate the SOA, the more useful SOA becomes as a predictor for firm performance. Having yearly or even quarterly SOA figures would present many new useful opportunities for researchers and investors alike.

7. Conclusion

Accurately estimating the speed of adjustment (SOA) of capital structure is one of the most important, yet difficult endeavors in capital structure research today (Huang and Ritter, 2009). Existing techniques, such as mean differencing and system GMM estimators with firm fixed effects, are fraught with biases. Through employing the long differencing estimator first introduced by Hahn et al. (2007), this thesis reduces these biases and shows that firms adjust back to their target capital structure at a moderate pace. With a differencing length of $k = 10$, the SOA is 20.9% per year for book leverage and 32.3% for market leverage. In other words, firms take 2.9 and 1.8 years respectively to remove half the effect of a shock to their target capital structure.

SOA inherently assumes there is a target capital structure, hence the highly statistically significant SOAs estimated in this study strongly support the trade-off theory. However, SOA is in not in and of itself enough to conclusively determine the validity of the trade-off theory. Some skeptics, such as Chang and Dasgupta (2009), downplay the use of mean reversion techniques like SOA as evidence of the trade-off theory. Nonetheless, while market timing and pecking order contribute to firms' capital structure compositions in the short-term, this thesis supports trade-off theory as the driving force behind firms' capital structure decisions over the long-term.

Additionally, this thesis importantly tests the long differencing estimator using several different long differencing lengths *k* on the same dataset of sample firms. Thus, providing a clearer picture of the true relationship between the long differencing length *k* and the SOA. If the long differencing length *k* is not long enough the bias caused by the highly persistent nature of leverage as a dependent variable will not be sufficiently reduced, thereby causing the long differencing estimator to overestimate the SOA. The long differencing length of *k* must reach a threshold of around 8 years before this bias is mitigated.

Huang and Ritter (2009) are the first to use the long differencing estimator to measure the SOA of capital structure. They only report the results for the 3^{rd} iteration because three iterations are deemed often sufficient by Hahn et al. (2007). By employing the long differencing estimator with up to six iterations, this thesis confirms that three iterations are sufficient for measuring the SOA. Furthermore, it is likely three iterations are sufficient for researchers who wish to use the long differencing estimator for other means.

By applying the long differencing estimator to examine how significant economic events, such as recessions, the financial crisis and coinciding great recession, and the dissolution of the American conglomerate era affect capital structure; this study takes a unique approach to providing insightful contributions to the field. The great recession is found to increase the long difference between both firms' book and market leverages, thus indicating its significant effect on firms' capital structure. The shift from internal financing and conglomerates to external capital markets and more streamlined firms during the 1980s is also shown to increase the long difference between firms' leverages, albeit only market leverages. With economic recessions also only proving significant for market leverage, this study indicates large economic events have a more pronounced effect on market leverage than book leverage.

Appendix A

Table 1
Estimates of the SOA in Empirical Studies of Capital Structure

Table 1 reports the estimated annual speed of adjustment (SOA) toward target leverage per year in existing empirical studies of capital structure. The annualized numbers from Kayhan and Titman (2007) are computed as the compounded annual speed that achieves the five-year SOA that they report in their Table 2, 41% for book leverage and 35% for market leverage (i.e., $0.90^5 = 0.59$, and $0.917^5 = 0.65$). The estimate from Antoniou et al. (2008) is for U.S. firms in their Table 5. Half-life is the number of years that the SOA implies for a firm to move halfway toward its target capital structure. NA is not available.

		Book Leverage		Market Leverage	
Article	Estimator	SOA	Half-Life	SOA	Half-Life
Fama and French (2002)	OLS ignoring firm fixed effects	10%a	6.6 years	7%a	9.6 years
		18%b	3.5 years	15%b	4.3 years
Kayhan and Titman (2007)	OLS ignoring firm fixed effects	10%	6.6 years	8.3%	8.0 years
Flannery and Rangan (2006)	Firm fixed effects, mean differencing estimator with an instrumental variable	34.2%	1.7 years	35.5%	1.6 years
Antoniou, Guney, and Paudyal (2008)	Firm fixed effects, system GMM	NA	NA	32.2%	1.8 years
Lemmon, Roberts, and Zender (2008)	Firm fixed effects, system GMM	25%	2.4 years	NA	NA
Huang and Ritter (2009)	Firm fixed effects, long differencing	17%	3.7 years	23.2%	2.6 years
This Thesis	Firm fixed effects, long differencing	20.9%	2.9 years	32.3%	1.8 years

a=Dividend-paying firms
b=Firms that do not pay dividends

Source: Huang and Ritter (2009)

Table 2

Descriptive Statistics for Firms with at least 7 Consecutive Years of Data

This table shows the descriptive statistics for firms with at least 7 consecutive years of data from 1961 – 2016, with a total of 63,187 observations. Book leverage is defined as book debt (items 181 + 10 – 35 – 79) divided by book assets (item 6). Market leverage is defined as book debt divided by market assets (items 181 + 10 – 35 + 25 x 199). Q is the sum of the market value of equity and the book value of debt divided by the book value of assets. R&D is the research and development expense (46) scaled by assets and is set to zero if it is missing. CAPEX is the capital expenditure (128). Note that there is only 1 observation for which R&D is negative and only 4 observations for which CAPEX is negative. Therefore, their effect is negligible. SALE is the log of net sales (12). OIBD is the operating income before depreciation (13). TANG is the net property, plant, and equipment (8). R&D, CAPEX, OIBD, and TANG are scaled by assets. ERP_{t-1} is the implied market equity risk premium at the end of year $t - 1$. RIR_{t-1} is the nominal interest rate at the end of year $t - 1$ minus inflation in year t. DSP_{t-1} is the default spread, defined as the difference in yields between Moody's Baa-rated and Aaa-rated corporate bonds at the end of year $t - 1$. TSP_{t-1} is the term spread, defined as the difference in yields (daily series) between ten- and one-year constant maturity Treasuries at the end of year $t - 1$. $TAXR_t$ is the statutory corporate tax rate during year t. $RGDP_t$ is the real GDP growth rate during year t (Huang and Ritter 2009).

	Mean	Median	S.D.	Min.	Max.	Skew	Kurtosis
BL	0.443	0.452	0.188	0.003	1.000	-0.002	-0.538
ML	0.389	0.377	0.226	0.001	1.000	0.250	-0.864
Q	1.513	1.151	1.299	0.028	111.508	14.297	861.424
R&D	0.023	0.000	0.057	-0.003	2.052	6.813	95.273
CAPEX	0.069	0.052	0.067	-0.021	1.367	3.076	20.096
Ln(SALE)	5.214	4.893	1.977	-6.908	13.073	0.573	0.404
OIBD	0.131	0.133	0.119	-4.267	1.937	-2.932	56.575
TANG	0.369	0.309	0.249	0.000	1.000	0.645	-0.605
ERP	0.041	0.038	0.011	0.021	0.065	0.504	-0.555
RIR	0.010	0.009	0.023	-0.042	0.058	0.007	-0.555
DSP	0.011	0.010	0.005	0.000	0.034	1.676	3.798
TSP	0.010	0.008	0.012	-0.014	0.034	-0.031	-0.628
TAXR	0.413	0.400	0.068	0.000	0.528	-0.063	-0.496
RGDP	0.031	0.035	0.021	-0.028	0.073	-0.576	0.061

Table 3
Long Differencing Estimation of the SOA toward Target Leverage with Varying k and Varying Minimum Number of Years per Firm

The long differencing estimator employs the following regression (See Appendix B for details) with firm data from 1961 – 2016**:**

$$L_{it} - L_{it-k} = \lambda(L_{it-1} - L_{it-k-1}) + \delta(X_{it-1} - X_{it-k-1}) + \tilde{\varepsilon}_{it} - \tilde{\varepsilon}_{it-k}$$

Rewritten as: $\Delta \mathrm{L}_{\mathrm{it,t-k}} = \lambda \Delta L_{it-1,t-k-1} + \delta \Delta X_{it-1,t-k-1} + \tilde{u}_{it,t-k}$

The dependent variable is the change in either book leverage or market leverage between the end of year t and the end of year $t - k$ of firm i ($k =$ 4, 8, 10, or 12). Book leverage is defined as book debt (items 181 + 10 – 35 – 79) divided by book assets (item 6). Market leverage is defined as book debt divided by market assets (items 181 + 10 – 35 + 25 x 199). X includes lagged firm characteristics, lagged or current market conditions, and dummy variables. Q is the sum of the market value of equity and the book value of debt divided by the book value of assets. R&D is the research and development expense (46) scaled by assets and is set to zero if it is missing. R&DD is a dummy variable that equals one if R&D is missing and equals zero otherwise. CAPEX is the capital expenditure (128). SALE is the log of net sales (12). OIBD is the operating income before depreciation (13). TANG is the net property, plant, and equipment (8). R&D, CAPEX, OIBD, and TANG are scaled by assets. ERP is the implied market equity risk premium at the end of year $t - 1$. RIR is the nominal interest rate at the end of year $t - 1$ minus inflation in year t. DSP is the default spread, defined as the difference in yields between Moody's Baa-rated and Aaa-rated corporate bonds at the end of year $t - 1$. TSP is the term spread, defined as the difference in yields (daily series) between ten- and one-year constant maturity Treasuries at the end of year $t - 1$. TAXR is the statutory corporate tax rate during year t. RGDP is the real GDP growth rate during year t (Huang and Ritter 2009). ERD is an economic recession dummy which equals one for years there was a recession and zero otherwise. The following recession years are used: 1970, 1974, 1975, 1980, 1981, 1982, 1990, 2001, 2008, 2009 (Hummel, 2015). GERD is a dummy variable for the great recession which equals one for the years 2008 and 2009 and a zero otherwise. CONGD is a dummy variable to compare the pre- and post-conglomerate eras. It equals one for the years 1980 – 1989 and zero otherwise. The t-statistics use heteroskedastic consistent standard errors, further adjusted for correlation across observations of a given firm (White (1980), Rogers (1993)). Panel A displays book leverage results and Panel B displays market leverage results.

	k = 4		k = 8		k = 10		k = 12	
Min. No. Years per Firm	7		11		13		15	
Panel A. Book Leverage	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat
$\Delta L_{it-1,t-k-1}$	0.603	106.2	0.756	149.8	0.786	157.1	0.809	159.7
$\Delta Q_{it-1,t-k-1}$	-0.006	-8.5	-0.006	-9.1	-0.005	-7.3	-0.004	-5.6
$\Delta R\&DD_{it-1,t-k-1}$	-0.006	-3.7	-0.004	-2.3	-0.004	-2.5	-0.002	-1.1
$\Delta R\&D_{it-1,t-k-1}$	0.023	0.9	-0.031	-1.0	-0.009	-0.2	-0.023	-0.6
$\Delta CAPEX_{it-1,t-k-1}$	0.077	6.5	0.070	6.5	0.081	7.2	0.059	5.2
$\Delta SALE_{it-1,t-k-1}$	0.016	14.1	0.010	11.7	0.008	10.1	0.004	5.3
$\Delta OIBD_{it-1,t-k-1}$	-0.248	-19.3	-0.252	-30.8	-0.242	-28.3	-0.250	-27.1
$\Delta TANG_{it-1,t-k-1}$	0.078	10.9	0.045	7.8	0.030	5.2	0.025	4.6
$\Delta ERP_{t-1,t-k-1}$	-0.299	-5.5	0.072	1.5	-0.055	-1.0	-0.063	-1.1
$\Delta RIR_{t-1,t-k-1}$	-0.137	-6.8	-0.128	-6.8	-0.084	-4.1	0.013	0.6
$\Delta DSP_{t-1,t-k-1}$	-0.963	-8.8	-1.674	-12.7	-1.767	-11.7	-1.332	-9.8
$\Delta TSP_{t-1,t-k-1}$	-0.513	-13.9	-0.399	-7.1	-0.519	-8.8	-0.479	-9.2
$\Delta TAXR_{t,t-k}$	-0.078	-5.2	-0.059	-4.0	-0.031	-2.2	-0.076	-5.3
$\Delta RGDP_{t,t-k}$	-0.057	-2.0	-0.027	-0.9	-0.179	-6.1	-0.033	-0.8
$\Delta ERD_{t,t-k}$	-0.004	-1.7	-0.003	-1.0	-0.001	-0.2	0.002	0.4
$\Delta GERD_{t,t-k}$	0.036	14.8	0.028	9.5	0.014	3.7	0.039	10.1
$\Delta CONGD_{t,t-k}$	0.000	-0.1	-0.001	-0.3	-0.005	-1.4	-0.005	-1.1
Adj. R^2	0.423		0.597		0.643		0.669	
N	63187		56418		52662		49746	
Panel B. Market Leverage	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat
$\Delta L_{it-1,t-k-1}$	0.515	95.2	0.651	128.3	0.669	129.2	0.716	128.1
$\Delta Q_{it-1,t-k-1}$	-0.016	-22.3	-0.014	-18.8	-0.012	-15.6	-0.011	-11.9
$\Delta R\&DD_{it-1,t-k-1}$	-0.031	-14.5	-0.024	-11.6	-0.018	-8.1	-0.013	-6.0
$\Delta R\&D_{it-1,t-k-1}$	-0.094	-4.0	-0.137	-5.2	-0.156	-5.2	-0.139	-3.8
$\Delta CAPEX_{it-1,t-k-1}$	0.117	8.3	0.150	11.5	0.164	11.8	0.169	11.8
$\Delta SALE_{it-1,t-k-1}$	0.044	34.8	0.031	32.0	0.024	26.0	0.015	15.8
$\Delta OIBD_{it-1,t-k-1}$	-0.299	-21.4	-0.334	-35.5	-0.344	-34.0	-0.327	-29.9
$\Delta TANG_{it-1,t-k-1}$	0.092	11.0	0.067	9.6	0.065	9.1	0.066	9.4
$\Delta ERP_{t-1,t-k-1}$	-2.454	-35.3	-1.384	-21.6	-1.192	-16.2	-1.184	-16.7
$\Delta RIR_{t-1,t-k-1}$	-0.976	-38.4	-1.048	-43.5	-0.898	-33.5	-0.895	-32.5
$\Delta DSP_{t-1,t-k-1}$	0.851	6.2	-0.342	-2.1	-0.810	-4.2	0.837	4.9
$\Delta TSP_{t-1,t-k-1}$	-0.875	-19.3	-0.751	-10.6	-0.435	-5.8	-1.307	-19.9
$\Delta TAXR_{t,t-k}$	0.079	4.3	0.331	17.7	0.343	19.5	0.173	9.7
$\Delta RGDP_{t,t-k}$	0.063	1.7	0.078	2.0	-0.311	-8.0	-0.131	-2.6
$\Delta ERD_{t,t-k}$	-0.018	-6.2	-0.036	-10.5	-0.005	-1.3	0.020	4.0
$\Delta GERD_{t,t-k}$	0.074	25.0	0.064	17.7	-0.015	-3.1	0.059	12.0
$\Delta CONGD_{t,t-k}$	0.040	14.1	0.041	11.8	0.036	8.0	-0.005	-1.0
Adj. R^2	0.441		0.597		0.631		0.659	
N	63187		56418		52662		49746	

Table 4

Long Differencing Estimation of the SOA toward Target Leverage with Varying *k* for Firms with a Minimum 20 Years of Data

The long differencing estimator employs the following regression (See Appendix B for details) using only firms which have a minimum of 20 years of consecutive data to mitigate the short time dimension bias and ensure all differencing lengths *k* use the same sample firms. This consists of firms from 1961 – 2016:

$$L_{it} - L_{it-k} = \lambda(L_{it-1} - L_{it-k-1}) + \delta(X_{it-1} - X_{it-k-1}) + \tilde{\varepsilon}_{it} - \tilde{\varepsilon}_{it-k}$$

$$\text{Rewritten as: } \Delta \mathrm{L}_{\mathrm{it,t-k}} = \lambda \Delta L_{it-1,t-k-1} + \delta \Delta X_{it-1,t-k-1} + \tilde{u}_{it,t-k}$$

The dependent variable is the change in either book leverage or market leverage between the end of year t and the end of year $t-k$ of firm i ($k=$ 4, 8, 10, or 12). Book leverage is defined as book debt (items 181 + 10 -35 – 79) divided by book assets (item 6). Market leverage is defined as book debt divided by market assets (items 181 + 10 – 35 + 25 x 199). X includes lagged firm characteristics, lagged or current market conditions, and dummy variables. Q is the sum of the market value of equity and the book value of debt divided by the book value of assets. R&D is the research and development expense (46) scaled by assets and is set to zero if it is missing. R&DD is a dummy variable that equals one if R&D is missing and equals zero otherwise. CAPEX is the capital expenditure (128). SALE is the log of net sales (12). OIBD is the operating income before depreciation (13). TANG is the net property, plant, and equipment (8). R&D, CAPEX, OIBD, and TANG are scaled by assets. ERP is the implied market equity risk premium at the end of year $t-1$. RIR is the nominal interest rate at the end of year $t-1$ minus inflation in year t. DSP is the default spread, defined as the difference in yields between Moody's Baa-rated and Aaa-rated corporate bonds at the end of year $t-1$. TSP is the term spread, defined as the difference in yields (daily series) between ten- and one-year constant maturity Treasuries at the end of year $t-1$. TAXR is the statutory corporate tax rate during year t. RGDP is the real GDP growth rate during year t (Huang and Ritter, 2009). ERD is an economic recession dummy which equals one for years there was a recession and zero otherwise. The following recession years are used: 1970, 1974, 1975, 1980, 1981, 1982, 1990, 2001, 2008, 2009 (Hummel, 2015). GERD is a dummy variable for the great recession which equals one for the years 2008 and 2009 and a zero otherwise. CONGD is a dummy variable to compare the pre- and post-conglomerate era. It equals one for the years 1980 – 1989 and zero otherwise. The t-statistics use heteroskedastic consistent standard errors, further adjusted for correlation across observations of a given firm (White (1980), Rogers (1993)). Panel A displays book leverage results and Panel B displays market leverage results.

	(1) k = 4		(2) k = 8		(3) k = 10		(4) k = 12	
Min. No. Years per Firm	20		20		20		20	
Panel A. Book Leverage	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat
$\Delta L_{it-1,t-k-1}$	0.616	107.6	0.765	148.7	0.791	157.6	0.811	159.9
$\Delta Q_{it-1,t-k-1}$	-0.003	-4.3	-0.005	-7.5	-0.004	-6.0	-0.003	-4.0
$\Delta R\&DD_{it-1,t-k-1}$	-0.003	-1.6	-0.005	-2.8	-0.005	-2.6	-0.004	-2.1
$\Delta R\&D_{it-1,t-k-1}$	-0.005	-0.2	-0.074	-2.4	-0.026	-0.8	-0.029	-0.8
$\Delta CAPEX_{it-1,t-k-1}$	0.099	9.4	0.064	6.0	0.070	6.4	0.049	4.3
$\Delta SALE_{it-1,t-k-1}$	0.010	8.7	0.005	5.8	0.005	6.7	0.002	2.3
$\Delta OIBD_{it-1,t-k-1}$	-0.259	-30.1	-0.246	-29.1	-0.249	-28.2	-0.244	-25.6
$\Delta TANG_{it-1,t-k-1}$	0.053	7.4	0.036	6.2	0.027	4.7	0.019	3.3
$\Delta ERP_{t-1,t-k-1}$	-0.383	-6.6	0.013	0.3	-0.071	-1.2	-0.051	-0.9
$\Delta RIR_{t-1,t-k-1}$	-0.132	-6.3	-0.098	-5.1	-0.057	-2.7	0.038	1.7
$\Delta DSP_{t-1,t-k-1}$	-0.835	-7.4	-1.521	-11.4	-1.759	-11.5	-1.284	-9.4
$\Delta TSP_{t-1,t-k-1}$	-0.464	-12.4	-0.398	-6.9	-0.498	-8.4	-0.495	-9.5
$\Delta TAXR_{t,t-k}$	-0.061	-4.0	-0.082	-5.5	-0.046	-3.3	-0.093	-6.5
$\Delta RGDP_{t,t-k}$	-0.092	-3.0	-0.022	-0.7	-0.158	-5.3	-0.037	-0.9
$\Delta ERD_{t,t-k}$	-0.006	-2.3	-0.002	-0.9	-0.001	-0.2	0.003	0.7
$\Delta GERD_{t,t-k}$	0.033	13.3	0.024	8.2	0.015	3.9	0.041	10.5
$\Delta CONGD_{t,t-k}$	0.002	0.6	0.000	-0.1	-0.004	-1.1	-0.006	-1.4
Adj. R^2	0.432		0.607		0.647		0.673	
N	40177		40177		40177		40177	
Panel B. Market Leverage	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat
$\Delta L_{it-1,t-k-1}$	0.522	92.9	0.661	125.6	0.677	128.8	0.723	133.0
$\Delta Q_{it-1,t-k-1}$	-0.014	-17.7	-0.014	-17.8	-0.012	-15.1	-0.010	-12.8
$\Delta R\&DD_{it-1,t-k-1}$	-0.025	-10.0	-0.022	-9.7	-0.017	-7.3	-0.013	-5.7
$\Delta R\&D_{it-1,t-k-1}$	-0.125	-3.3	-0.146	-4.1	-0.154	-4.2	-0.117	-3.0
$\Delta CAPEX_{it-1,t-k-1}$	0.162	12.0	0.147	10.9	0.163	11.5	0.175	12.1
$\Delta SALE_{it-1,t-k-1}$	0.039	28.1	0.025	24.4	0.021	21.3	0.012	12.9
$\Delta OIBD_{it-1,t-k-1}$	-0.351	-33.1	-0.341	-32.6	-0.355	-32.8	-0.321	-27.7
$\Delta TANG_{it-1,t-k-1}$	0.064	7.3	0.069	9.4	0.066	9.0	0.061	8.6
$\Delta ERP_{t-1,t-k-1}$	-2.204	-29.4	-1.233	-18.4	-1.183	-15.5	-1.154	-15.9
$\Delta RIR_{t-1,t-k-1}$	-0.939	-34.7	-0.995	-40.1	-0.864	-31.4	-0.860	-30.8
$\Delta DSP_{t-1,t-k-1}$	0.906	6.3	-0.275	-1.6	-0.525	-2.6	0.913	5.3
$\Delta TSP_{t-1,t-k-1}$	-0.843	-17.6	-0.870	-11.8	-0.529	-6.9	-1.307	-19.8
$\Delta TAXR_{t,t-k}$	0.108	5.6	0.272	14.1	0.303	16.9	0.154	8.6
$\Delta RGDP_{t,t-k}$	0.091	2.3	0.163	4.0	-0.271	-6.9	-0.118	-2.3
$\Delta ERD_{t,t-k}$	-0.010	-2.9	-0.031	-8.5	-0.002	-0.5	0.023	4.6
$\Delta GERD_{t,t-k}$	0.072	23.2	0.067	17.9	-0.012	-2.3	0.062	12.5
$\Delta CONGD_{t,t-k}$	0.033	10.5	0.037	10.0	0.031	6.7	-0.009	-1.7
Adj. R^2	0.448		0.605		0.636		0.664	
N	40177		40177		40177		40177	

Table 5

Long Differencing Estimator Iterations and the SOA toward Target Leverage

The previous Tables 3 and 4 report the results of the third iteration of the long differencing estimator as Hahn et al. (2007) suggest that three iterations are often sufficient. This table reports the results for the fourth, fifth, and sixth iterations of the long differencing estimator in addition to the third iteration for comparison. Only firms with a minimum of 20 years of consecutive data are used and all of the iterations use k = 10. This consists of firms from 1961 – 2016**.** The long differencing estimator employs the following regression (See Appendix B for details):

$$L_{it} - L_{it-k} = \lambda(L_{it-1} - L_{it-k-1}) + \delta(X_{it-1} - X_{it-k-1}) + \tilde{\varepsilon}_{it} - \tilde{\varepsilon}_{it-k}$$

$$\text{Rewritten as: } \Delta \mathrm{L}_{\mathrm{it,t-k}} = \lambda \Delta L_{it-1,t-k-1} + \delta \Delta X_{it-1,t-k-1} + \tilde{u}_{it,t-k}$$

The dependent variable is the change in either book leverage or market leverage between the end of year t and the end of year $t-k$ of firm i ($k =$ 4, 8, 10, or 12). Book leverage is defined as book debt (items 181 + 10 – 35 – 79) divided by book assets (item 6). Market leverage is defined as book debt divided by market assets (items 181 + 10 – 35 + 25 x 199). X includes lagged firm characteristics, lagged or current market conditions, and dummy variables. Q is the sum of the market value of equity and the book value of debt divided by the book value of assets. R&D is the research and development expense (46) scaled by assets and is set to zero if it is missing. R&DD is a dummy variable that equals one if R&D is missing and equals zero otherwise. CAPEX is the capital expenditure (128). SALE is the log of net sales (12). OIBD is the operating income before depreciation (13). TANG is the net property, plant, and equipment (8). R&D, CAPEX, OIBD, and TANG are scaled by assets. ERP is the implied market equity risk premium at the end of year $t-1$. RIR is the nominal interest rate at the end of year $t-1$ minus inflation in year t. DSP is the default spread, defined as the difference in yields between Moody's Baa-rated and Aaa-rated corporate bonds at the end of year $t-1$. TSP is the term spread, defined as the difference in yields (daily series) between ten- and one-year constant maturity Treasuries at the end of year $t-1$. TAXR_t is the statutory corporate tax rate during year t. RGDP is the real GDP growth rate during year t (Huang and Ritter, 2009). ERD is an economic recession dummy which equals one for years there was a recession and zero otherwise. The following recession years are used: 1970, 1974, 1975, 1980, 1981, 1982, 1990, 2001, 2008, 2009 (Hummel, 2015). GERD is a dummy variable for the great recession which equals one for the years 2008 and 2009 and a zero otherwise. CONGD is a dummy variable to compare the pre- and post-conglomerate era. It equals one for the years 1980 – 1989 and zero otherwise. The t-statistics use heteroskedastic consistent standard errors, further adjusted for correlation across observations of a given firm (White (1980), Rogers (1993)). Panel A displays book leverage results and Panel B displays market leverage results.

	k = 10		k = 10		k = 10		k = 10	
Min. No. Years per Firm	20		20		20		20	
No. of Iterations	[3]		[4]		[5]		[6]	
Panel A. Book Leverage	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat
$\Delta L_{it-1,t-k-1}$	0.791	157.6	0.792	157.6	0.791	157.6	0.792	157.6
$\Delta Q_{it-1,t-k-1}$	-0.004	-6.0	-0.004	-6.0	-0.004	-6.0	-0.004	-6.0
$\Delta R\&DD_{it-1,t-k-1}$	-0.005	-2.6	-0.005	-2.6	-0.005	-2.6	-0.005	-2.6
$\Delta R\&D_{it-1,t-k-1}$	-0.026	-0.8	-0.026	-0.8	-0.026	-0.8	-0.026	-0.8
$\Delta CAPEX_{it-1,t-k-1}$	0.070	6.4	0.070	6.4	0.070	6.4	0.070	6.4
$\Delta SALE_{it-1,t-k-1}$	0.005	6.7	0.005	6.7	0.005	6.7	0.005	6.7
$\Delta OIBD_{it-1,t-k-1}$	-0.249	-28.2	-0.249	-28.2	-0.249	-28.2	-0.249	-28.2
$\Delta TANG_{it-1,t-k-1}$	0.027	4.7	0.027	4.7	0.027	4.7	0.027	4.7
$\Delta ERP_{t-1,t-k-1}$	-0.071	-1.2	-0.071	-1.2	-0.071	-1.2	-0.071	-1.2
$\Delta RIR_{t-1,t-k-1}$	-0.057	-2.7	-0.057	-2.7	-0.057	-2.7	-0.057	-2.7
$\Delta DSP_{t-1,t-k-1}$	-1.759	-11.5	-1.759	-11.4	-1.759	-11.4	-1.759	-11.4
$\Delta TSP_{t-1,t-k-1}$	-0.498	-8.4	-0.499	-8.4	-0.498	-8.4	-0.499	-8.4
$\Delta TAXR_{t,t-k}$	-0.046	-3.3	-0.046	-3.3	-0.046	-3.3	-0.046	-3.3
$\Delta RGDP_{t,t-k}$	-0.158	-5.3	-0.158	-5.3	-0.158	-5.3	-0.158	-5.3
$\Delta ERD_{t,t-k}$	-0.001	-0.2	-0.001	-0.2	-0.001	-0.2	-0.001	-0.2
$\Delta GERD_{t,t-k}$	0.015	3.9	0.015	3.9	0.015	3.9	0.015	3.9
$\Delta CONGD_{t,t-k}$	-0.004	-1.1	-0.004	-1.1	-0.004	-1.1	-0.004	-1.1
Adj.R^2	0.647		0.647		0.647		0.647	
N	40177		40177		40177		40177	
Panel B. Market Leverage	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat
$\Delta L_{it-1,t-k-1}$	0.677	128.8	0.678	128.9	0.678	128.8	0.678	128.9
$\Delta Q_{it-1,t-k-1}$	-0.012	-15.1	-0.012	-15.1	-0.012	-15.1	-0.012	-15.1
$\Delta R\&DD_{it-1,t-k-1}$	-0.017	-7.3	-0.017	-7.3	-0.017	-7.3	-0.017	-7.3
$\Delta R\&D_{it-1,t-k-1}$	-0.154	-4.2	-0.154	-4.2	-0.154	-4.2	-0.154	-4.2
$\Delta CAPEX_{it-1,t-k-1}$	0.163	11.5	0.163	11.5	0.163	11.5	0.163	11.5
$\Delta SALE_{it-1,t-k-1}$	0.021	21.3	0.021	21.3	0.021	21.3	0.021	21.3
$\Delta OIBD_{it-1,t-k-1}$	-0.355	-32.8	-0.355	-32.8	-0.355	-32.8	-0.355	-32.8
$\Delta TANG_{it-1,t-k-1}$	0.066	9.0	0.066	9.0	0.066	9.0	0.066	9.0
$\Delta ERP_{t-1,t-k-1}$	-1.183	-15.5	-1.183	-15.5	-1.183	-15.5	-1.183	-15.5
$\Delta RIR_{t-1,t-k-1}$	-0.864	-31.4	-0.865	-31.5	-0.865	-31.5	-0.865	-31.5
$\Delta DSP_{t-1,t-k-1}$	-0.525	-2.6	-0.519	-2.6	-0.521	-2.6	-0.520	-2.6
$\Delta TSP_{t-1,t-k-1}$	-0.529	-6.9	-0.530	-6.9	-0.530	-6.9	-0.530	-6.9
$\Delta TAXR_{t,t-k}$	0.303	16.9	0.303	16.9	0.303	16.9	0.303	16.9
$\Delta RGDP_{t,t-k}$	-0.271	-6.9	-0.270	-6.9	-0.271	-6.9	-0.270	-6.9
$\Delta ERD_{t,t-k}$	-0.002	-0.5	-0.002	-0.5	-0.002	-0.5	-0.002	-0.5
$\Delta GERD_{t,t-k}$	-0.012	-2.3	-0.012	-2.3	-0.012	-2.3	-0.012	-2.3
$\Delta CONGD_{t,t-k}$	0.031	6.7	0.031	6.7	0.031	6.7	0.031	6.7
Adj. R^2	0.636		0.636		0.636		0.636	
N	40177		40177		40177		40177	

Table 6

Instrumental Variable Regressions for Increasing Iterations of the Long Differencing Estimator

Using the valid instruments $\Delta L_{it-1,t-k-1}$, *Residual 1 (R1), and R2… R10,* the following regression is run as part of the 2SLS process used in the Long Differencing Estimator from Table 5:

$$\Delta L_{it,t-10} = \beta_0 \Delta L_{it-1,t-11} + \beta_1 R1 + \beta_2 R2 + \cdots + \beta_3 R10 + \tilde{u}_{it,t-10}$$

For every year *t* there are 10 residuals as additional instruments.

$$Residual\ 1 = \Delta L_{it,t-1} - \hat{\lambda}\Delta L_{it-1,t-2} - \hat{\delta}_0 \Delta Q_{it-1,t-2} - \cdots - \hat{\delta}_{15} \Delta CONGD_{it,t-1}$$

$$Residual\ 2 = \Delta L_{it,t-2} - \hat{\lambda}\Delta L_{it-1,t-3} - \hat{\delta}_0 \Delta Q_{it-1,t-3} - \cdots - \hat{\delta}_{15} \Delta CONGD_{it,t-2}$$

.
.
.

$$Residual\ 10 = \Delta L_{it,t-10} - \hat{\lambda}\Delta L_{it-1,t-11} - \hat{\delta}_0 \Delta Q_{it-1,t-11} - \cdots - \hat{\delta}_{15} \Delta CONGD_{it,t-10}$$

These instrumental variable regressions are explained in steps 7 – 13 of the Long Differencing Estimator in *Appendix B.* The V.I. in front of $\Delta L_{it-1,t-k-1}$ stands for valid instrument to differentiate it from the $\Delta L_{it-1,t-k-1}$ in Tables 3 – 5.

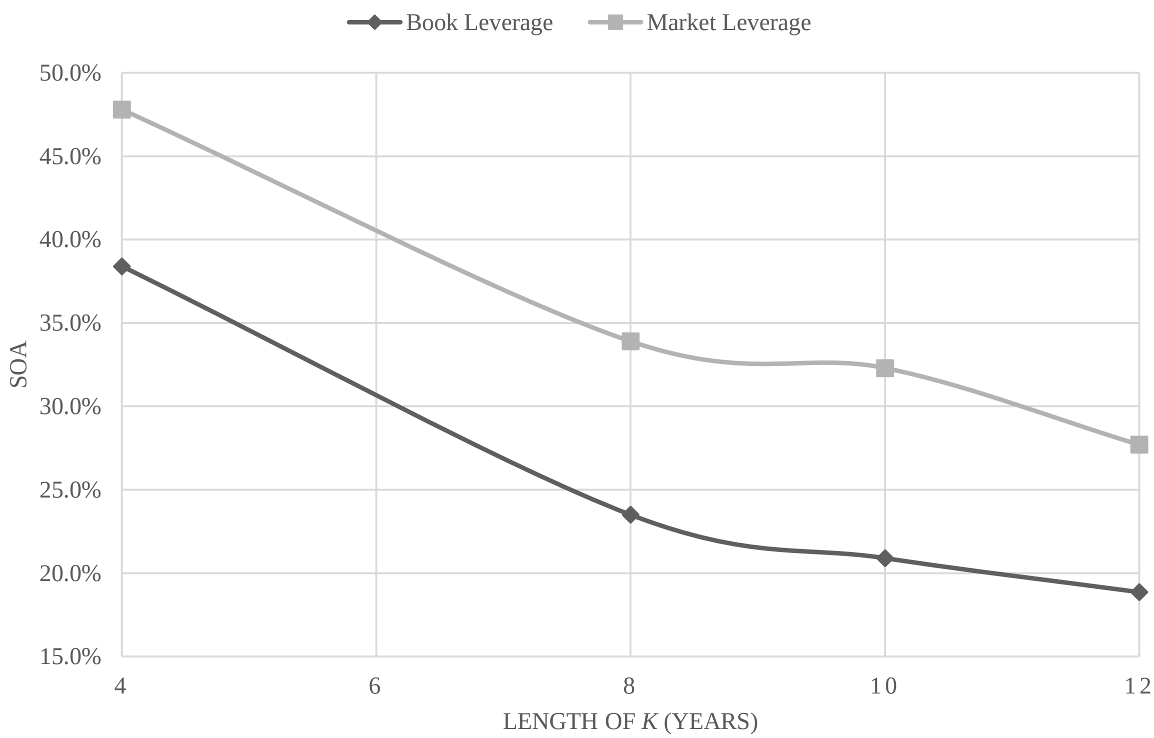
	k = 10		k = 10		k = 10		k = 10	
Min. No. Years per Firm		20		20		20		20
No. of Iterations		[3]		[4]		[5]		[6]
Panel A. Book Leverage	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat
V.I. $\Delta L_{it-1,t-k-1}$	0.841	576.9	0.842	577.8	0.842	577.3	0.842	577.6
R1	0.029	8.1	0.029	8.1	0.029	8.1	0.029	8.1
R2	0.043	12.3	0.043	12.3	0.043	12.3	0.043	12.3
R3	0.033	9.8	0.033	9.8	0.033	9.8	0.033	9.8
R4	0.023	7.0	0.023	7.0	0.023	7.0	0.023	7.0
R5	0.012	3.5	0.012	3.5	0.012	3.5	0.012	3.5
R6	-0.002	-0.5	-0.002	-0.5	-0.002	-0.5	-0.002	-0.5
R7	-0.014	-4.4	-0.014	-4.4	-0.014	-4.4	-0.014	-4.4
R8	-0.040	-11.9	-0.040	-12.0	-0.040	-12.0	-0.040	-12.0
R9	-0.063	-19.0	-0.063	-19.0	-0.063	-19.0	-0.063	-19.0
R10	0.934	285.4	0.934	285.5	0.934	285.4	0.934	285.5
Adj. R^2	0.968		0.968		0.968		0.968	
N	40177		40177		40177		40177	
Panel B. Market Leverage	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat
V.I. $\Delta L_{it-1,t-k-1}$	0.836	436.7	0.837	437.3	0.836	437.0	0.836	437.2
R1	0.079	17.8	0.080	17.9	0.079	17.8	0.079	17.8
R2	0.062	14.3	0.063	14.3	0.063	14.3	0.063	14.3
R3	0.040	9.4	0.040	9.4	0.040	9.4	0.040	9.4
R4	0.030	7.2	0.030	7.2	0.030	7.2	0.030	7.2
R5	0.020	4.7	0.020	4.7	0.020	4.7	0.020	4.7
R6	0.020	4.8	0.020	4.8	0.020	4.8	0.020	4.8
R7	-0.006	-1.5	-0.007	-1.6	-0.007	-1.6	-0.007	-1.6
R8	-0.099	-23.4	-0.099	-23.4	-0.099	-23.4	-0.099	-23.4
R9	-0.121	-28.6	-0.121	-28.6	-0.121	-28.6	-0.121	-28.6
R10	0.893	213.9	0.893	213.9	0.893	213.9	0.893	213.9
Adj. R^2	0.933		0.933		0.933		0.933	
N	40177		40177		40177		40177	

Figure 1
Table 4 SOA in Relation to Increasing Lengths of *k*

Figure 1 displays the long differencing estimator SOAs from Table 4. The same sample set of firms with a minimum of 20 years of consecutive data are used for all lengths of *k*. This consists of firms from 1961 – 2016 with 40,177 observations. The SOA is calculated by $(1-\lambda)$ from the long differencing estimator:

$$L_{it} - L_{it-k} = \lambda(L_{it-1} - L_{it-k-1}) + \delta(X_{it-1} - X_{it-k-1}) + \tilde{\varepsilon}_{it} - \tilde{\varepsilon}_{it-k}$$

$$\text{Rewritten as: } \Delta \mathrm{L}_{\mathrm{it,t-k}} = \lambda \Delta L_{it-1,t-k-1} + \delta \Delta X_{it-1,t-k-1} + \tilde{u}_{it,t-k}$$



Appendix B

The Long Differencing Estimator

The process used in this thesis to estimate the speed of adjustment (SOA) from the long differencing estimator is based upon the descriptions by Hahn et al. (2007) and Huang and Ritter (2009). The long differencing estimator is a series of 2SLS which utilizes instrumental variables and estimates the following equation:

(A-1) $L_{it} - L_{it-k} = \lambda(L_{it-1} - L_{it-k-1}) + \delta(X_{it-1} - X_{it-k-1}) + \tilde{\varepsilon}_{it} - \tilde{\varepsilon}_{it-k}$

Or

(A-2) $\Delta L_{it,t-k} = \lambda \Delta L_{it-1,t-k-1} + \delta \Delta X_{it-1,t-k-1} + \tilde{u}_{it,t-k}$

The dependent variable, $\Delta L_{it,t-k}$, is the change in either book leverage, BL_{it}, or market leverage, ML_{it}, between the end of year t and the end of year $t-k$ of firm i. k is the length of the "long difference." Both in (A-1) and the shortened notation version (A-2) $(1-\lambda)$ represents the SOA. X_{it} represents all of the other independent variables for company *i* at time *t* besides the lagged leverage. These variables are the following:

$$\Delta Q_{it-1,t-k-1}, \Delta R\&DD_{it-1,t-k-1}, \Delta R\&D_{it-1,t-k-1}, \Delta CAPEX_{it-1,t-k-1}, \Delta SALE_{it-1,t-k-1},$$

$$\Delta OIBD_{it-1,t-k-1}, \Delta TANG_{it-1,t-k-1}, \Delta ERP_{t-1,t-k-1}, \Delta RIR_{t-1,t-k-1}, \Delta DSP_{t-1,t-k-1},$$

$$\Delta TSP_{t-1,t-k-1}, \Delta TAXR_{t,t-k}, \Delta RGDP_{t,t-k}, \Delta ERD_{t,t-k}, \Delta GERD_{t,t-k}, \Delta CONGD_{t,t-k}$$

The dummy variables are also differenced as done by Huang and Ritter (2009).

<u>Step 1:</u>

$\Delta L_{it-1,t-k-1}$ in (A-2) will be replaced with a predicted leverage value that is uncorrelated with the error terms by using an instrumental variable. Hahn et al. (2007) suggest $\Delta L_{it-1,t-k-1}$ is a valid instrument for $\Delta L_{it,t-k}$. Using pooled OLS, the relationship between $\Delta L_{it-1,t-k-1}$ and $\Delta L_{it,t-k}$ is estimated through the regression:

(A-3) $\Delta L_{it,t-k} = \beta \Delta L_{it-1,t-k-1} + \tilde{u}_{it,t-k}$

The Breusch-Pagan Lagrange Multiplier test is used to determine that pooled OLS is the most suitable for this regression (Baltagi et al. 1990). All of the other regressions in the coming steps that utilize valid instruments also are estimated through pooled OLS.

<u>Step 2:</u>

The estimated coefficient $\hat{\beta}$ is saved from regression (A-3).

Step 3:

Using $\hat{\beta}$ from regression (A-3) new predicted values of $\Delta L_{it,t-k}$ are created.

(A-4) $\Delta\widehat{L_{it,t-k}} = \hat{\beta}(\Delta L_{it-1,t-k-1})$

Equation (A-4) is not a regression, but a calculation that consists of multiplication to predict values of $\Delta L_{it,t-k}$ that are uncorrelated to the error terms of (A-2). Note that $\hat{\beta}$ remains constant, while $\Delta L_{it-1,t-k-1}$ changes for firm and year.

Step 4:

$\Delta\widehat{L_{it,t-k}}$ from (A-4) is lagged one year to become $\Delta L_{\widehat{it-1,t-}k-1}$ and replaces $\Delta L_{it-1,t-k-1}$ in (A-2). $\left(\Delta L_{\widehat{it-1,t-k-1}}\right)_0$ will be designated with the subscript 0 to eliminate confusion in the succeeding steps.

Step 5:

The long differencing estimator regression (A-2) is run using pooled OLS and $\left(\Delta L_{\widehat{it-1,t-k-1}}\right)_0$ as a substitute for $\Delta L_{it-1,t-k-1}$:

(A-5) $\Delta L_{it,t-k} = \lambda\left(\Delta L_{\widehat{it-1,t-k-1}}\right)_0 + \delta_0 \Delta Q_{it-1,t-k-1} + \cdots + \delta_{15}\Delta CONGD_{t,t-k} + \tilde{u}_{it,t-k}$

Step 6:

The estimated coefficients $\hat{\lambda}$, and $\hat{\delta}_0$ ... $\hat{\delta}_{15}$ are saved from regression (A-5).

Step 7:

In steps 1 through 5 the single instrument $\Delta L_{it-1,t-k-1}$ is used in a 2SLS process culminating in running the (A-5) regression. However, for the long differencing estimator to have less bias additional instruments are used. These additional instruments are the residuals from the actual differenced leverages compared to the differenced leverages as predicted by the long differencing estimator for each lagged year of the long difference from 1 to *k* (Hahn et al., 2007). This means that for every year *t* there are *k* residuals as additional instruments.

$$Residual\ 1 = \Delta L_{it,t-1} - \hat{\lambda}\Delta L_{it-1,t-2} - \hat{\delta}_0 \Delta Q_{it-1,t-2} - \cdots - \hat{\delta}_{15}\Delta CONGD_{t,t-1}$$

$$Residual\ 2 = \Delta L_{it,t-2} - \hat{\lambda}\Delta L_{it-1,t-3} - \hat{\delta}_0 \Delta Q_{it-1,t-3} - \cdots - \hat{\delta}_{15}\Delta CONGD_{t,t-2}$$

.
.
.

$$Residual\ k = \Delta L_{it,t-k} - \hat{\lambda}\Delta L_{it-1,t-k-1} - \hat{\delta}_0 \Delta Q_{it-1,t-k-1} - \cdots - \hat{\delta}_{15}\Delta CONGD_{t,t-k}$$

These residuals require the use of the estimated coefficients $\hat{\lambda}$, and $\hat{\delta}_0$ ... $\hat{\delta}_{15}$ from step 6. Steps 1 through 5 are necessary preliminary steps so the full amount of instruments are able to be used in the long differencing estimator. Note that $\hat{\lambda}$, and $\hat{\delta}_0$ ... $\hat{\delta}_{15}$ remain constant in the calculation of the residuals while the differenced variables change for firm and year.

Step 8:

Using the valid instruments $\Delta L_{it-1,t-k-1}$, *Residual 1 (R1), and R2… Rk,* the following regression is run using pooled OLS:

(A-6) $\Delta L_{it,t-k} = \beta_0 \Delta L_{it-1,t-k-1} + \beta_1 R1 + \beta_2 R2 + \cdots + \beta_k Rk + \tilde{u}_{it,t-k}$

Step 9:

The estimated coefficients $\hat{\beta}_0$, $\hat{\beta}_1, and\ \hat{\beta}_2$ ... $\hat{\beta}_k$ are saved from regression (A-6).

Step 10:

Using $\hat{\beta}_0$, $\hat{\beta}_1, and\ \hat{\beta}_2$ ... $\hat{\beta}_k$ from equation (A-6) new predicted values of $\Delta L_{it,t-k}$ are created for the second time.

(A-7) $\Delta \widehat{L_{\imath t,t-k}} = \hat{\beta}_0 \left(\Delta L_{it-1,t-k-1}\right) + \hat{\beta}_1 (R1) + \hat{\beta}_2 (R2) + \cdots + \hat{\beta}_k (Rk)$

Equation (A-7) is not a regression, but a calculation that consists of addition and multiplication to predict values of $\Delta L_{it,t-k}$ that are uncorrelated to the error terms of (A-2). Note that $\hat{\beta}_0$, $\hat{\beta}_1, and\ \hat{\beta}_2$ ... $\hat{\beta}_k$ remain constant, while $\Delta L_{it-1,t-k-1}$, *R1*, and *R2 … Rk* change for firm and year.

Step 11:

$\Delta \widehat{L_{\imath t,t-k}}$ from (A-7) is lagged one year to become $\left(\Delta \widehat{L_{\imath t-1,t-k-1}}\right)_1$ and replaces $\Delta L_{it-1,t-k-1}$ in (A-2).

Step 12:

The long differencing estimator regression (A-2) is run using pooled OLS and $\left(\Delta \widehat{L_{\imath t-1,t-k-1}}\right)_1$ as a substitute for $\Delta L_{it-1,t-k-1}$:

(A-8) $\Delta L_{it,t-k} = \lambda_1 \left(\Delta \widehat{L_{\imath t-1,t-k-1}}\right)_1 + \delta_{0_1} \Delta Q_{it-1,t-k-1} + \cdots + \delta_{15_1} \Delta CONGD_{t,t-k} + \tilde{u}_{it,t-k}$

Step 13:

The estimated coefficients $\hat{\lambda}_1$, and $\hat{\delta}_{0_1}$ ... $\hat{\delta}_{15_1}$ are saved from regression (A-8). The coefficients are all designated with a subscript 1 because these results are the end of iteration 1. One iteration consists of steps 7 through 13. The purpose of each iteration is to create better and better residuals as additional instruments to increase the adjusted R^2 of the instrumental variable equation, and thereby produce better and better predicted $\Delta \widehat{L_{\imath t-1,t-k-1}}$ to replace $\Delta L_{it-1,t-k-1}$ in (A-2).

Step 14:

The estimated coefficients $\hat{\lambda}_1$, and $\hat{\delta}_{0_1}$ ... $\hat{\delta}_{15_1}$ from regression (A-8) are used to create a new set of residuals that are used as instruments. The residuals are created in the same process as step 7.

Steps 15 - 18:

Same process as steps 8 - 11.

Step 19:

The long differencing estimator regression (A-2) is run using pooled OLS and $\left(\Delta L_{\widehat{\imath t-1,t-}k-1}\right)_2$ as a substitute for $\Delta L_{it-1,t-k-1}$:

(A-9) $\Delta L_{it,t-k} = \lambda_2\left(\Delta L_{\widehat{\imath t-1,t-}k-1}\right)_2 + \delta_{0_2}\Delta Q_{it-1,t-k-1} + \cdots + \delta_{15_2}\Delta CONGD_{t,t-k} + \tilde{u}_{it,t-k}$

Step 20:

The estimated coefficients $\hat{\lambda}_2$, and $\hat{\delta}_{0_2}$ ... $\hat{\delta}_{15_2}$ are saved from regression (A-9) and are the results of iteration 2.

Steps 21 – 25:

Same process as steps 14 – 18 except using the estimated coefficients $\hat{\lambda}_2$, and $\hat{\delta}_{0_2}$ ... $\hat{\delta}_{15_2}$ from regression (A-9) to create the residuals.

Step 26:

The long differencing estimator regression (A-2) is run using pooled OLS and $\left(\Delta L_{\widehat{\imath t-1,t-}k-1}\right)_3$ as a substitute for $\Delta L_{it-1,t-k-1}$:

(A-9) $\Delta L_{it,t-k} = \lambda_3\left(\Delta L_{\widehat{\imath t-1,t-}k-1}\right)_3 + \delta_{0_3}\Delta Q_{it-1,t-k-1} + \cdots + \delta_{15_3}\Delta CONGD_{t,t-k} + \tilde{u}_{it,t-k}$

Step 27:

The estimated coefficients $\hat{\lambda}_3$, and $\hat{\delta}_{0_3}$ ... $\hat{\delta}_{15_3}$ are saved from regression (A-9) and are the results of iteration 3. The results from the 3rd iteration are reported in *Tables 3 and 4* because Hahn et al. (2007) suggest that 3 iterations are often sufficient. $(1 - \hat{\lambda}_3)$ is the SOA. However, *Table 5* reports the results from 4, 5, and 6 iterations to explore if there are any improvements from using more iterations.

Appendix C: Long Differencing Estimator R Code for Estimation of SOA

The following R code corresponds to the long differencing estimator theory described in Appendix B. The entire code is for a single long differencing estimate of the SOA . This example code is the SOA estimate for market leverage (ML) with a differencing length of k = 8 and 3 iterations of the long differencing estimator process . The code was written in consultation with Patrick Herrod , B.A. DePauw University M.S. Purdue University, for his expertise in R. Additionally, the article "Panel Data Econometrics in R: the plm Package," by Croissant and Millo (2008) was used for guidance and the White's Correction code is from this article.

```
#install necessary packages,
install.packages("readxl")
install.packages("plm")
install.packages("plyr")
install.packages("foreach")
install.packages("doParallel")
install.packages("car")
install.packages("lmtest")

# Load dependencies
library(readxl)
library(plm)
library(plyr)
library(parallel)
library(Formula)
library(iterators)
library(foreach)
library(doParallel)
library(lmtest)

options(warn=-1)        # Command to turn off warning messages, so that output
    is more easily readable

# Load excel file into R
my data <- read excel("/Users/Administrator/Desktop/Final 11 Year Data.xlsx")

#### ——— beginning of script logic ——— ####

# Calculate the number of host system cores
no_cores <- detectCores() - 1

# Initiate parallel computing cluster
cl <- makeCluster(no_cores)
setDefaultCluster(cl)
registerDoParallel(cl)

# set variables before processing
lag <- 8 # 8-year lag
iterations <- 3 # LD iterations
iv_var <- "ML"  # independent variable definition

# Print variables to use in Algorithm
cat("Lag: ", lag, "\n", sep='')
cat("LD iterations: ", iterations, "\n", sep='')
cat("IV : ", iv_var, "\n", sep='')

lag_vars <- c(iv_var,"Q","RnD","CAPEX","SALE","OIBD","TANG","ERP","RIR","DSP","
    TSP","RnDD") # selecting the correct columns to diff from tibble
curr_vars <- c(iv_var,"TAXR","RGDP","ERD","GERD","CONGD") # select current
    variables to diff

# —— Variables for different plm formulas —— #
if(iv_var == "ML") {
```

```
        plm.dl <- as.formula("D_ML ~ D_LML - 1")
        plm.Rs <- "D_ML ~ D_LML"
} else {
        plm.dl <- as.formula("D_BL ~ D_LBL - 1")
        plm.Rs <- "D_BL ~ D_LBL"
}
for (i in 1:lag) {
        plm.Rs <- paste(plm.Rs, " + R",i,sep='')          # build Residual formula
}
plm.Rs <- paste(plm.Rs, " - 1", sep='') # append "-1" to Residual formula
plm.Rs <- as.formula(plm.Rs)
D <- " + D Q + D RnD + D CAPEX + D SALE + D OIBD + D TANG + D ERP + D RIR + D
   DSP + D TSP + D RnDD + D TAXR + D RGDP + D ERD + D GERD + D CONGD - 1"  #
   append necessary columns to Long Differencing formula

keys <- unique(my data$CUSIP) # store all unique CUSIPs in a list

# Function to separate data by company
split companies <- function(x, data) {
        return (data[data$CUSIP == x,])
}

# Differencing function
diff func <- function(y) {
        diff(y, lag)
}

# Helper function to handle special column cases and determine how to diff the
   rows for each company
wrapper <- function(x) {
        a <- head(x[lag vars], -1) # remove the last row for lag diff of ML-TSP
        res <- apply(a, 2, diff func) # perform diff on lag vars, excluding the
            last row
        b <- tail(x[curr vars], -1) # remove first row prior to diff cur vars
        res2 <- apply(b, 2, diff func) # perform diff on lag vars (ML-RGDP
            columns), excluding the first row
        index <- tail(x[,1:2],-(lag+1)) # keep, but shrink index columns
        res <- cbind(index, res, res2) # join (and order) all columns together
        return (res)
}

# Create special case of instrumental variable "zero"
create iv0 <- function(d) {
        if(iv_var == "ML") {    # determine the selected iv
                ND_ML <- sapply(d$D_LML, function(z, slope) {    # iterate
                    through company data by D_ML column values
                        return (z*slope)                 # calculate D_ML *
                            regression slope
                }, regres_slope)
                IV0 <- c(NA, head(ND_ML, -1))    # create separate IV column,
                    removing the first row
                res <- cbind(ND_ML, IV0)                 # store both ND_ML and
                    IV0 columns
        } else {
                ND_BL <- sapply(d$D_LBL, function(z, slope) {    # iterate
                    through company data by D_BL column values
                        return (z*slope)                 # calculate D_BL *
                            regression slope
                }, regres_slope)

                IV0 <- c(NA, head(ND_BL, -1))    # create separate IV column,
```

```
                removing the first row
            res <- cbind(ND_BL, IV0)                # store both ND_ML and
                IV0 columns
        }
        return (res)    # return caculated columns
}

# Function to extract and store the regression coefficients
# this function is dependant on the order of the data's columns
est_coefficients <- function(p) {
        iv <- unname(p[1])                      # strip each value of it's "name
            " and store in a variable
        d_q <- unname(p[2])
        d_rnd <- unname(p[3])
        d_capex <- unname(p[4])
        d_sale <- unname(p[5])
        d_oidb <- unname(p[6])
        d_tang <- unname(p[7])
        d_erp <- unname(p[8])
        d_rir <- unname(p[9])
        d_dsp <- unname(p[10])
        d_tsp <- unname(p[11])
        d_rndd <- unname(p[12])
        d_taxr <- unname(p[13])
        d_rgdp <- unname(p[14])
        d_erd <- unname(p[15])
        d_gerd <- unname(p[16])
        d_congd <- unname(p[17])
        est_coeff <- data.frame(cbind(
                iv,     # add variables to data frame for ease-of-access
                d_q,
                d_rnd,
                d_capex,
                d_sale,
                d_oidb,
                d_tang,
                d_erp,
                d_rir,
                d_dsp,
                d_tsp,
                d_rndd,
                d_taxr,
                d_rgdp,
                d_erd,
                d_gerd,
                d_congd))
        return (est_coeff)              # return resulting data frame
}

# Function to calculate all residuals for one row of company data
row_residuals <- function(row) {
        num_resids <- c(1:lag)
        res <- laply(num_resids, calc_residuals, row, my_data, iv_var, est_coeff
            ) # calculate the Residual and iterate to calculate all residuals

        if(iv_var == "ML") {
                res <- c(row$CUSIP, row$Year, row$D_ML, row$D_LML, res) # add
                    CUSIP, Year, D_ML, and D_LML to calulated residual
                res_names <- c("CUSIP", "Year", "D_ML", "D_LML")
                    # name the columns
        } else {
```

```
        res <- c(row$CUSIP, row$Year, row$D_BL, row$D_LBL, res)
        res_names <- c("CUSIP", "Year", "D_BL", "D_LBL")
    }
    for (i in 1:lag) {
        res_names <- c(res_names, paste("R", i, sep=''))        # name
            each calculated residual
    }
    names(res) <- res_names          # set the column names
    return (res)                     # return the result
}


# Function to calculate a single residual
calc_residuals <- function(r, row, my_data, iv_var, est_coeff) {
    r_lag <- 1+r                # set lag based on which R to calculate
    curr_data_row <- my_data[my_data$CUSIP == row$CUSIP & my_data$Year ==
        row$Year,]              # get raw data row that matches the row
        passed to this function
    lag_year_data_row <- my_data[my_data$CUSIP == row$CUSIP & my_data$Year
        == (row$Year-1),]       # get raw data row the that matches one year
         prior to the row passed to this function
    subtrahend_data_row <- my_data[my_data$CUSIP == row$CUSIP & my_data$Year
         == (row$Year-r_lag),] # get raw data row that mathces lagged years
        prior to row passed to this function (subtrahend for lagged coeffs)

    # Calculate and store lambda - delta15 (values needed to calculate
        residual)
    # Difference the data values, then multiply with corresponding
        regression coefficients
    if(iv_var == "ML") {
        lambda <- est_coeff$iv*(lag_year_data_row$ML - subtrahend_data_
            row$ML)
    } else {
        lambda <- est_coeff$iv*(lag_year_data_row$BL - subtrahend_data_
            row$BL)
    }
    delta0 <- est_coeff$d_q*(lag_year_data_row$Q - subtrahend_data_row$Q)
    delta1 <- est_coeff$d_rnd*(lag_year_data_row$RnD - subtrahend_data_row$
        RnD)
    delta2 <- est_coeff$d_capex*(lag_year_data_row$CAPEX - subtrahend_data_
        row$CAPEX)
    delta3 <- est_coeff$d_sale*(lag_year_data_row$SALE - subtrahend_data_row
        $SALE)
    delta4 <- est_coeff$d_oidb*(lag_year_data_row$OIBD - subtrahend_data_row
        $OIBD)
    delta5 <- est_coeff$d_tang*(lag_year_data_row$TANG - subtrahend_data_row
        $TANG)
    delta6 <- est_coeff$d_erp*(lag_year_data_row$ERP - subtrahend_data_row$
        ERP)
    delta7 <- est_coeff$d_rir*(lag_year_data_row$RIR - subtrahend_data_row$
        RIR)
    delta8 <- est_coeff$d_dsp*(lag_year_data_row$DSP - subtrahend_data_row$
        DSP)
    delta9 <- est_coeff$d_tsp*(lag_year_data_row$TSP - subtrahend_data_row$
        TSP)
    delta10 <- est_coeff$d_rndd*(lag_year_data_row$RnDD - subtrahend_data_
        row$RnDD)
    subtrahend_data_row <- my_data[my_data$CUSIP == row$CUSIP & my_data$Year
         == (row$Year-r),] #reset subtrahend for non-lagged coefficients
    if(iv_var == "ML") {
        ml_sub <- (curr_data_row$ML - subtrahend_data_row$ML)
```

```
    } else {
        bl_sub <- (curr_data_row$BL - subtrahend_data_row$BL)
    }
    delta11 <- est_coeff$d_taxr*(curr_data_row$TAXR - subtrahend_data_row$
      TAXR)
    delta12 <- est_coeff$d_rgdp*(curr_data_row$RGDP - subtrahend_data_row$
      RGDP)
    delta13 <- est_coeff$d_erd*(curr_data_row$ERD - subtrahend_data_row$ERD)
    delta14 <- est_coeff$d_gerd*(curr_data_row$GERD - subtrahend_data_row$
      GERD)
    delta15 <- est_coeff$d_congd*(curr_data_row$CONGD - subtrahend_data_row$
      CONGD)

    # Calculate residual, subtracting terms from lagged ml or bl
    if(iv_var == "ML") {
        R <- ml_sub - lambda - delta0 - delta1 - delta2 - delta3 -
          delta4 - delta5 - delta6 - delta7 - delta8 - delta9 - delta10
          - delta11 - delta12 - delta13 - delta14 - delta15
    } else {
        R <- bl_sub - lambda - delta0 - delta1 - delta2 - delta3 -
          delta4 - delta5 - delta6 - delta7 - delta8 - delta9 - delta10
          - delta11 - delta12 - delta13 - delta14 - delta15
    }
    return (R)      # return R result
}

# General function to create an instrumental variable
create_iv <- function(data) {
    d <- adply(data, 1, create_nd, regres_slope, .expand=F)       #
      iterate over company data by row and calculate ND
    if(iv_var == "ML") {
        IV <- c(NA, head(d$ND_ML, -1))       # create IV column
          removing the first row
    } else {
        IV <- c(NA, head(d$ND_BL, -1))
    }
    d <- cbind(d, IV)                    # combine N and IV columns
    return (d)                  # return result
}

# Function to create ND varible
create_nd <- function(z, slope) {
    if(iv_var == "ML") {
        D_LML_term <- slope * z$D_LML
        ND_ML <- D_LML_term
    } else {
        D_LBL_term <- slope * z$D_LBL
        ND_BL <- D_LBL_term
    }
    RS <- lapply(1:lag, function(i) {                         #
      iterate over Rs
        return (unname(regres$coefficients[i+1]) * z[[paste("R",i,sep=''
          )]])    # multiply regression coefficient and corresponding R
          value
    })
    RS <- Reduce("+",RS)           # reduce Rs to one value by summation
    if(iv_var == "ML") {           # finish calculation and return data
      frame
        ND_ML <- ND_ML + RS
        return (data.frame(ND_ML))
    } else {
```

```
                ND_BL <- ND_BL + RS
                return (data.frame(ND_BL))
        }
}

# --- Main processing --- #
clusterExport(cl, list("lag", "lag_vars", "curr_vars", "diff_func", "cl"), envir
   =environment())

split_data <- parLapply(cl, keys, split_companies, my_data) # create a tibble(
   very much like a table) with data separated by company
result <- parLapply(cl, split_data, wrapper) # process each company tibble and
   return resulting values, to view results in r studio simply type "results"
result <- do.call(rbind, result) # combine the tibbles
if(iv_var == "ML") {
        colnames(result) <- c("CUSIP","Year","D_LML","D_Q","D_RnD","D_CAPEX","D_
           SALE","D_OIBD","D_TANG","D_ERP","D_RIR","D_DSP","D_TSP","D_RnDD","D_
           ML","D_TAXR","D_RGDP","D_ERD","D_GERD","D_CONGD") # give result data
            appropriate column names
} else {
        colnames(result) <- c("CUSIP","Year","D_LBL","D_Q","D_RnD","D_CAPEX","D_
           SALE","D_OIBD","D_TANG","D_ERP","D_RIR","D_DSP","D_TSP","D_RnDD","D_
           BL","D_TAXR","D_RGDP","D_ERD","D_GERD","D_CONGD") # give result data
            appropriate column names
}
pdata <- plm.data(result, c("CUSIP", "Year")) # cast data to pdata for panel
   regression
regres <- plm(plm.dl,  data=pdata, model="pooling") # run regression
regres_slope <- unname(regres$coefficients[1])          # remove extra infor and
     store regression slope
split_data <- parLapply(cl, keys, split_companies, result) # split data from
   result table NOT my_data
IV0 <- adply(split_data, 1, create_iv0, .parallel=T, .paropts=.(.export=c("iv_
   var", "regres_slope")))$IV0        # compute ND_ML and IV0 variables
result <- cbind(result, IV0)    # add ND_ML and IV0 columns to results table
pdata <- plm.data(result, c("CUSIP", "Year")) # cast data to pdata for panel
   regression
if(iv_var == "ML") {
        L <- paste("D_ML ~ IV", 0, sep='')
} else {
        L <- paste("D_BL ~ IV", 0, sep='')
}
plm.LD <- as.formula(paste(L,D,sep=''))                 # build long
   differencing formula
LD_0 <- plm(plm.LD, data=pdata, model="pooling")                # run first long
     difference
est_coeff <- est_coefficients(LD_0$coefficients)                # store long
   difference coefficients
residuals <- adply(split_data, 1, function(tibble) {            # iterate over
   all data to calculate residuals
        return (adply(tibble, 1, row_residuals, .expand=F, .id=NULL))    #
            iterate over each companies data by row
}, .expand=F, .id=NULL, .parallel=T, .paropts=.(.export=c("row_residuals", "calc
   _residuals", "my_data", "iv_var", "est_coeff")))        # set parameters and
   variables for outer iteration to run in parallel
assign("RS_1", residuals)                               # create variable for
   first round of residual values
pdata <- plm.data(residuals, c("CUSIP", "Year"))
regres <- plm(plm.Rs, data=pdata, model="pooling")              # run regression
     over first residuals
cat("Iteration: 1", "\n", sep="")
```

```
print(regres)
regres_slope <- unname(regres$coefficients[1])          # store new regression
    slope
split_residuals <- parLapply(cl, keys, split_companies, residuals)
    # split residuals by CUSIP
for (i in 1:iterations) {
        IV <- adply(split_residuals, 1, create_iv, .expand=F, .id=NULL, .
            parallel=T, .paropts=.(.export=c("create_nd", "iv_var", "regres_slope
            ", "regres")))$IV          # calculate IV in parallel
        assign(paste("IV", i, sep=''), IV)              # store IV according to
            the iteration number
        result <- cbind(result, IV)                     # add IV to result table
        colnames(result)[length(colnames(result))] <- paste("IV",i,sep='')
                    # rename current IV column according to iteration number
        pdata <- plm.data(result, c("CUSIP", "Year"))   # cast data to pdata for
             panel regression
        if(iv_var == "ML") {
                L <- paste("D_ML ~ IV", i, sep='')
        } else {
                L <- paste("D_BL ~ IV", i, sep='')
        }
        plm.LD <- as.formula(paste(L,D,sep=''))
        LD <- plm(plm.LD, data=pdata, model="pooling")                    #
            perform Long Difference
        assign(paste("LD_",i,sep=''), LD)
                    # create LD variable for current iteration
        est_coeff <- est_coefficients(LD$coefficients)                    # store
            LD coefficients
        residuals <- adply(split_data, 1, function(tibble) {
                            # iterate over data by company to calculate residuals
                return (adply(tibble, 1, row_residuals, .expand=F, .id=NULL))
                            # iterate over each row in company data to calculate
                    residual
        }, .expand=F, .id=NULL, .parallel=T, .paropts=.(.export=c("row_residuals
            ", "calc_residuals", "my_data", "iv_var", "est_coeff")))
                    # set parameters and variables for outer iteration to run in
            parallel
        assign(paste("RS_",i,sep=''), residuals)                          # store
            residual values for current iteration
        pdata <- plm.data(residuals, c("CUSIP", "Year"))
        regres <- plm(plm.Rs, data=pdata, model="pooling")                # run
            regression on Residuals
        assign(paste("regres_",i,sep=''), regres)                         # store
            residual regression for this iteration
        cat("Iteration: ", i, "\n", sep="")
        print(regres)
        regres_slope <- unname(regres$coefficients[1])          # store
            iteration regression slope
}


# White's Correction
coeftest(LD_3, vcov = pvcovHC(LD_3, method = "white2", type = "HC3"))

# Stop and release cluster
stopImplicitCluster()
stopCluster(cl)
```

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Master Thesis

Component of continuous assessment: Forprosjekt, Thesis MSc

Speed of Adjustment of Capital Structure and its Value as a Predictor of Firm Performance

ID number:	0985961, 0988826
Start:	01.12.2016 09.00
Finish:	01.03.2017 12.00

0985961
0988826

Preliminary Thesis Report

Speed of Adjustment of Capital Structure and its Value as a Predictor of Firm Performance

Hand-in date:
01.03.2017

Examination code and name:

GRA 19502 Master Thesis

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Introduction

In speaking about the theories of capital structure as is known today, it is important to understand what preceded the development of the trade-off, pecking order and market-timing theories. The Modigliani and Miller Theorem (1958) of the irrelevance of capital structure essentially birthed this school of thought and as noted by Frank and Goyal (2007), "Before them, there was no generally accepted theory of capital structure." There are some contentions that this idea did not begin with the 1958 paper. Williams (1938) in his paper, The Theory of Investment value, makes a statement about the idea but does not present arbitrage-based proof (Frank & Goyal 2007).

Modigliani and Miller (1958) started with the assumption of a firm having a set of expected cash flows. When the firm decides on the proportion of debt and equity it will use to finance itself, all that it does is to divide up the cash flows among investors. In this framework, investors and firms are assumed to have equal access to financial markets, which allows for homemade leverage. By this assumption, the investor can create any leverage that was wanted but not offered, or the investor can get rid of any leverage that the firm took on but was not wanted. As a result, the leverage of the firm has no effect on the market value of the firm (Frank and Goyal, 2007).

At the time of this paper, it stimulated a lot of interest within the topic, with many researchers setting out to disprove the theory. Ultimately, via this research, it was seen that the Modigliani and Miller theorem fails under a variety of circumstances. The most commonly referenced include consideration of taxes, transaction costs, bankruptcy costs, agency conflicts, adverse selection, lack of separability between financing and operations, time-varying financial market opportunities, and investor clientele effects. (Frank and Goyal, 2007)

The Trade-off Theory

This theory is an off-shoot the previous model presented by Modigliani and Miller. As was put forward by Myers (1984), a firm's optimal debt ratio is determined by trade-off of the costs and benefits of borrowing, holding the firm's assets and investment plans constant. Firms in this structure are balancing the value of interest tax shields against bankruptcy costs (Myers, 1984). Incorporating corporate tax into the original irrelevance proposition, a benefit for debt was seen because it shielded earnings from taxes. Given that the firm's objective, this implies that firms should be 100% debt-financed, given the lack of a counterbalancing cost of debt. It is for this reason that the cost of bankruptcy is used in this framework (Frank and Goyal, 2007).

The theory of optimal leverage reflects a trade-off between the tax benefits of debt and the deadweight costs of bankruptcy (Kraus and Litzenberger, 1973). Myers (1984) also added that a firm that follows the trade-off theory sets a target debt-to-value ratio and then gradually moves towards the target. The target is determined by balancing debt tax shields against costs of bankruptcy (Frank and Goyal, 2007). This forms the basis of the trade-off theory.

Pecking Order Theory

Fama and French (2002) assert this theory, developed or revised to some extent by Myers (1984) arises if the cost of issuing new securities overwhelm the costs and benefits of dividend and debt. The pecking theory states that when a company needs to finance itself, it should first look internally and do so via retained earnings. If this source of financing is available, debt should then be utilized to satisfy its financing needs. The issue of equity for the purpose of financing the company should be the last option.

The financing costs that produce behavior supportive of pecking order theory include the transaction costs associated with new issues. In addition the costs that arise due to information asymmetry must be considered because of management's superior information about the firm's prospects i.e. positive NPV projects in the pipeline and equally important the value of its risky security. These reasons, according to Fama and French (2002), result in the financing of new investments by firms "first with retained earnings, then with safe debt, then with risky debt, and finally, under duress, with equity."

The intuition behind this "pecking order" of methods of financing projects is in part due to what signals each source of finance sends to the market. If the company is funding itself, the signal is that it has the cash to do so and believes the project is an NPV positive one. This is a signal of financial health. Funding through the use of debt intimates that the management of the company and the market is comfortable that the company would be able to service the subsequent debt payments. Use of equity, could be potentially viewed as a negative, as it might give the appearance of the company cashing in on stock they might view as overvalued.

Market Timing Theory

The theory asserts that management issue securities depending on the time-varying relative costs of debt and equity and the issue of these have long-lasting effects on capital structure (Huang and Ritter, 2009). According to two of its main proponents, “capital structure is the cumulative outcome of past attempts to time the equity markets.” (Baker and Wurgler, 2002) In their 2002 paper, they investigated whether equity timing after capital structure and ultimately if there is a short-run or long-run impact.

Their results indicated that market-timing had large, persistent affects on capital structure. More importantly, they concluded that low leverage firms are those that raised funds for investment in projects when their market valuations were high. Conversely, high leverage firms are those that raised firms when their market valuations are low (Baker and Wurgler, 2002).

These results were not without its critics. Alti (2006) argued that even though Baker and Wurgler found persistent effects on leverage that extend beyond 10 years, one can critique their market timing measure. The proxy for long-term growth traits of firms is a history of concurrent increases in external funding needs and market-to-book ratios. Contemporaneous control variables are noisy proxies and likely resulted in a spurious relationship between history and capital structure. Hovakimian (2006) found contradictory results, finding no long-term effects for past equity market timing on market-to-book ratios.

Speed of Adjustment and Trade-off Theory

Under trade-off theory management seeks to maintain a target leverage because imperfections in the market mean the capital structure of a firm affects its value (Flannery and Rangan 2006). Various factors can push a firm off of its target leverage. The rate at which the firm adjusts back to its target leverage is known as the speed of adjustment (SOA). According to Graham and Leary (2011), this deviation from target leverage is a reason traditional trade-off models often produce little explanatory power. Therefore, SOA offers a way to test the validity of the trade-off theory by taking into account these deviations. SOA assumes that there is an actual target leverage, in contrast to theories such as market timing and pecking order. Huang and Ritter (2009) believe that SOA is perhaps the most important issue in capital structure research today. If firms actively adjust back to a target leverage over time then capital structure decisions based on market timing will only have short-term effects. Mean reversion to a target leverage would not exist for either market timing or pecking order. SOA therefore supports trade-off theory as the predominant force behind a firm's capital structure decisions over market timing and other theories that do not assume target leverage (Flannery and Rangan 2006). Although, it is important to note that some researchers do not believe that mean reversion alone adequately proves firms seek a target capital structure (Graham and Leary 2011).

Existing Work on the Speed of Adjustment

Many of the past studies on SOA use a partial-adjustment model to estimate the average SOA for firms as a whole. This method inherently assumes the average SOA is the same across all firms (Elsas and Florysiak 2011). Under this method much of the research primarily supports the trade-off theory by concluding that firms do have targets (Faulkender et al. 2011). However, evidence for market timing and pecking order is not completely absent. Huang and Ritter (2009) state that their estimates of the SOA toward target debt ratios suggest that firms do move toward target debt ratios, but their results imply that market timing and pecking also order contribute to the capital structure of firms. Flannery and Rangan (2006) find support for market timing and pecking order as well, although it is minimal in comparison to the support they find for trade-off theory. Targeting behavior displayed by firms accounted for over 50% of their capital structure changes compared to not even 10% for market timing and pecking order. The evidence that firms actively sought target leverage is strong for various firm sizes, time periods, and for book and market-valued leverage ratios. Market timing and pecking order are statistically significant in their study, but have their effect overwhelmed by firms' efforts to obtain a target leverage.

However, as noted by Frank and Goyal (2008), while corporate leverage is mean reverting at the firm level the speed of adjustment to the target is by no means a settled issue. Graham and Leary (2011) agree that despite the amount of existing research the rate of mean reversion is still an open question. They feel that the current body of SOA studies is not strong enough to say that firms actively manage to a target leverage. A reason for this is that the SOA's are mismeasured and the partial-adjustment models used are biased. *Table 1* displays the SOA's from some of the more notable studies. For book leverage the SOA ranges from 10% by Fama and French (2002) with a half-life of 6.6 years, to 34.2 % by Flannery and Rangan (2006) with a half-life of 1.7 years. For market leverage Fama and French (2002) again have the slowest SOA at 7% with a half-life of 9.6 years compared to Flannery and Rangan's (2006) SOA of 35.5% and half-life of 1.6 years. Eight years is a massive difference in the length of time it would take a firm to remove half of the effect of a shock on its leverage. Indeed, as Graham and Leary (2011) pointed out, the problem of biases in the measurement of adjustment speeds is a significant problem and one of the contributing factors to the wide range of SOA's.

Under reasonable assumptions an OLS estimated coefficient of the partial-adjustment model, as used by Fama and French (2002) and Kayhan and Titman (2007), that ignores firm fixed effects is biased upwards, meaning it will underestimate the SOA (Huang and Ritter 2009). It is no coincidence, therefore, that Fama and French (2002) have the slowest SOA. Some researchers believe that one reason for mismeasurement in SOA is ignoring firm fixed effects because the regular determinants for target leverage are producing unexplained variations. However, adding firm fixed effects makes consistently estimating the SOA difficult due to their presence in the error (Graham and Leary 2011). Mean differencing estimators with firm fixed effects and system GMM estimators with firm fixed effects are biased downwards, meaning it will overestimate the SOA (Huang and Ritter 2009). Consequently, Flannery and Rangan

(2006) have the highest SOA using a fixed effects estimator. Fortunately, the opposite biases of the OLS and fixed effects estimators allow the SOA to be approximately bounded and a range established (Graham and Leary 2011).

In an attempt to reduce the bias, Huang and Ritter (2009) employ a new econometric technique known as a long differencing estimator. This technique was first proposed by Hahn, Hausman, and Kuersteiner (2007) and theoretically helps reduce the bias caused when the dependent variable is highly persistent, such as with leverage ratios. Huang and Ritter (2009) state that estimates using the long difference method are less biased than the OLS estimator that ignores fixed effects except in the case the true SOA is very slow; however, in this scenario neither method would have much bias. Likewise, the long difference estimator is less biased than the firm fixed effects estimators except when the true SOA is very fast, although in this case neither estimator would have much bias. With the long differencing technique Huang and Ritter (2009) find an SOA of 17.0% for book leverage with a half – life of 3.7 years and a SOA of 23.2% for market leverage with a half-life of 2.6 years.

All of the models mentioned so far have been partial-adjustment models, which have come under criticism for biased estimates of coefficients and for a poor ability to differentiate leverage targeting from other financial motives (Graham and Leary 2011, Shyam-Sunder & Myers 1999, Chang & Dasgupta 2009). A dynamic panel data with a fractional dependent variable estimator (DPF) as proposed by Elsas and Florysiak (2010) takes a different approach than partial-adjustment models. While partial-adjustment models assume homogeneity in the speed of adjustment across all firms, the DPF estimator allows for heterogeneity across the speed of adjustment for firms. Elsas and Florysiak (2011) argue that given adjustment costs are often specific to firms and investments, the speed of adjustment is also often not homogeneous. The DPF estimator proposed by Elsas and Florysiak (2010) is constructed to be unbiased with unbalanced dynamic panel data. Elsas and Florysiak (2011) go on to run simulations that corroborate their claim that it is unbiased. There have not been many studies allowing for heterogeneity in SOA, with Faulkender et. Al (2010) and Dang et al. (2009) being some of the more notable. However, Elsas and Florysiak (2011) address more heterogeneous characteristics into their model than either of those. The SOA's estimated by Elsas and Florysiak (2011) vary, with some being as high as 60%.

Our Contribution and Plan of Action

This thesis contributes to the field through three stages. In stage 1 we will estimate the overall SOA and compare it to existing results. In stage 2 we will examine which firm characteristics can explain the cross-sectional variance of firm specific SOA. Finally, in stage 3 we will test the value of SOA as a predictor for firm performance.

Stage 1: Estimating Overall SOA

Stage 1 consists of estimating the SOA across all firms assuming homogeneity and comparing it to previous estimations done in articles such as Huang and Ritter (2009), Flannery and Rangan (2006), Fama and French (2002), and Kayhan and Titman (2007). This is important because there is far from a consensus in the literature on SOA due to the difficulty in predicting target leverage, the short time dimension bias, and the large econometric biases between the partial-adjustment models. At present, the best that has been done is to determine the bounds between which the true SOA may lie. Estimating the overall SOA and comparing it to existing results will bring more clarity to the issue and, in conjunction, provide more insight into the trade-off theory of capital structure. Given the known difficulties with biases, we will be doing more econometric work before deciding on a final model/models to use for this stage, but the long differencing estimator employed by Huang and Ritter (2009) looks promising.

The dependent variables will be the change in book leverage, total debt/total assets (TDA) and the change in market leverage, total debt/market value of total assets (TDM). For predicting target leverage, we created a sample data set out of variables commonly used for this purpose as in Rajan and Zingales (1995), Hovakimian (2003), Hovakimian, Opler and Titman (2001), Fama and French (2002). The variables are: EBIT/TDA, market-to-book value of assets (MB), depreciation & amortization (D&A)/TA, Fixed Assets (FA)/TA, property plant & equipment is used as fixed assets, and research and development (R&D)/TA (Flannery and Rangan 2006). This is a preliminary data set and the final partial-adjustment model will likely consist of more variables. The data set itself is discussed more in depth in the Data section.

Stage 2: Characteristics of Firm Specific SOA

In stage 2 we move beyond assuming homogeneous SOA to looking for the firm characteristics that can explain the heterogeneity of firm specific SOA. As Graham and Leary (2011) state, new methods outside the partial-adjustment framework may be necessary to identify the circumstances under which firms make deliberate, value-relevant financing decisions and when they fail to do so. Drawing from dynamic capital structure theory, if adjustment costs are specific to firms, then it follows their SOA would be heterogeneous as well. Our contribution will be important because more research has been needed in the field to understand what really drives the differences between firm's SOA (Elsas and Florysiak 2011). Understanding the key firm drivers of SOA will provide management teams with valuable insight into what their firms needs to do to position themselves to dynamically adjust to their capital structure targets in the appropriate time frame.

At this point, estimating a variation of the fractional dependent estimator (DPF) as proposed by Elsas and Florysiak (2010) looks to be a worthwhile route to take. The firm characteristics we are looking to investigate to that explain cross-sectional variance in SOA are: cash flows, difference between over and under levered firms, default risk (financial distress), large/small average financing deficits, financial constraints, market timing variables, and the sign and magnitude of the deviance from target leverage. Previous literature supports the use of these characteristics such as when Faulkender et al. (2011) demonstrated that cash flows have a significant effect on adjusting leverage and encouraged future research to incorporate the potentially compounding effects cash flows and the differences between over and under leveraged firms. We have not created a data set of these variables at this point.

Stage 3: SOA's value as a predictor of firm performance

This presents an opportunity to advance and shape future discussions on how SOAs can be utilised more effectively, beyond its current more passive interpretation as empiric evidence of the trade-off theory. Investigating the value of SOA as a predictor from a practical sense could potentially be utilized by managers as a signal to the market, thus reducing some of the information asymmetry that exists between the company and the market.

Whilst this is the stage we feel we can make the biggest contribution. It is also the section that at this point is the most underdeveloped due to the challenges posed in the first two stages. A challenge that we hope to overcome within the coming months. As a first step, we would need to link our calculated SOAs and known financial metrics that are already in use in the prediction of firm performance. Regressions come to mind for this stage. The relationship between SOA and ROA, for example, could be examined, as the ROA is one of the traditionally used metrics as a proxy for firm performance.

This stage, however, does not come without its obvious pitfalls. Given the nature of stages 1 and 2, stage 3 builds upon that. Given the estimations on top of estimation, misspecifications in the earlier stages can lead to less reliable or, in a worst case scenario, no discernible relationships between the calculated SOAs and the chosen metrics that are being estimated. Therefore, we must be careful of the compounding effect of econometric biases.

Also, the issue of endogeneity, must be overcome. It is easy to see the likelihood of endogeneity, when considering what is being attempted. In a regression involving ROA and SOA, it would be difficult to conclusively say whether ROA affects SOA or vice versa. The companies that are doing well are the most likely candidates to be able to effectively adjust their capital structure to a target leverage and thus would likely have a higher SOA as they are able to absorb the very material costs of adjustment. At the same time, companies that have higher SOAs might benefit from higher ROAs (if relationship is found to exist). The main issue is the potential lack of clarity of the true direction of the relationship.

Assuming that we are able to successfully overcome these issues thought would then have to be placed into the metrics used for evaluation of the predictive model and comparison metrics.

Data

This data set includes the independent and dependent variables to be used in Part 1 (estimating the overall SOA) of the thesis. The dynamic panel data sample consists of Compustat quarterly North American firm data from 1969 to 2016. Regulated enterprises (SIC 4900-4999) and financial services (SIC 6000-6999) are not included in the sample because their capital decisions may reflect special factors (Flannery and Rangan 2006). After trimming the data of any blank variable information there are 161,688 quarterly data points. The descriptive statistics can be found in *Table 2***.** The min, max, and standard deviations of several of the variables are quite extreme, in particular those of TDA, market to book, EBIT/TA, and R&D/TA. Additionally, many of the variables have a very large amount of skewness and kurtosis. The large sample size of firms taken across such a long period of time likely produced severe outliers that affected the data.

Issues with the TA may be at the root of several of the variable extremes because it is used as the divisor. The TDA also seems to be less stable than the TDM as it has a much larger dispersion between its mean and median. This may be another clue that there is something wrong with the total assets. The data was further trimmed to see the effects of eliminating any quarters with zero total debt *Table 3*. This left 53,741 quarterly data points. While still extreme results, this trimming of the data improve the results somewhat. For example, the standard deviation (SD) of the market-to-book ratio decreased by 27%. However, the data is still quite extreme and it is clear that a more thorough and exact cleaning of the data is required before the data could be used to estimate the overall SOA, run statistical tests, and make inferences.

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Appendix

Table 1: Estimates of the SOA in Empirical Studies of Capital Structure

Table 8 reports the estimated annual speed of adjustment (SOA) toward target leverage per year in existing empirical studies of capital structure. The annualized numbers from Kayhan and Titman (2007) are computed as the compounded annual speed that achieves the five-year SOA that they report in their Table 2, 41% for book leverage and 35% for market leverage (i.e., 0.905 = 0.59, and 0.91 75 = 0.65). The estimate from Antoniou et al. (2008) is for U.S. firms in their Table 5. Half-life is the number of years that the SOA implies for a firm to move halfway toward its target capital structure. NA is not available.

		Book Leverage		Market Leverage	
Article	Estimator	SOA	Half-Life	SOA	Half-Life
Fama and French (2002)	OLS ignoring firm fixed effects	10%a	6.6 years	7%a	9.6 years
		18%b	3.5 years	15%b	4.3 years
Kayhan and Titman (2007)	OLS ignoring firm fixed effects	10%	6.6 years	8.30%	8.0 years
Flannery and Rangan (2006)	Firm fixed effects, mean differencing estimatorwith an instrumental variable	34.20%	1.7 years	35.50%	1.6 years
Antoniou, Guney, and Paudyal (2008)	Firm fixed effects, system GMM	NA	NA	32.20%	1.8 years
Lemmon, Roberts, and Zender (2008)	Firm fixed effects, system GMM	25%	2.4 years	NA	NA
Huang and Ritter (2009)	Firm fixed efffects, long differencing	17%	3.7 years	23.20%	2.6 years

a=Dividend-paying firms
b=Firms that do not pay dividends

Source: Huang and Ritter (2009)

Table 2: Descriptive Statistics for all Observations

This table shows the descriptive statistics for all 161,688 observations. TDA is the total debt to total assets. TDM is the total debt to market value of assets. MVA is calculated as *the market value of equity MVE +debt in current liabilities + long-term debt – deferred taxes and investment tax credit (preferred stock liquidating value was not quarterly available in Compustat)*. MB is the market-to-book value of assets. EBIT is calculated as *revenue – operating costs* and EBIT/TA is EBIT divided by total assets. D&A/TA is the depreciation and amortization divided by total assets. Ln(TA) is the natural log of total assets. FA/TA is the fixed assets, calculated as property, plant, and equipment, divided by total assets. R&D/TA is the research and development costs divided by total assets.

	Mean	SD	Median	Min.	Max.	Skew	Kurtosis
TDA	0.97	29	0.12	0	5319	102.48	13826
TDM	0.17	0.49	0.07	-157.47	62.11	-200.11	70251
MB	19.72	843.89	1.54	-0.66	233779	179.05	42892
EBIT/TA	-0.34	24.11	0.02	-9017	44.33	-328.12	121153
D&A/TA	0.02	0.2	0.01	-0.14	70	280.48	94173
Ln(TA)	4.42	2.63	4.31	-6.91	13.08	-0.03	0.63
FA/TA	0.47	0.8	0.35	0	102	45.55	3932
R&D/TA	0.16	22.27	0.02	-6.92	8825	385.38	152553

Table 3: Descriptive Statistics for Trimmed Observations

This table shows the descriptive statistics for the trimmed dataset after quarters with zero total debt were excluded. There are 53,741 observations. TDA is the total debt to total assets. TDM is the total debt to market value of assets. MVA is calculated as *the market value of equity MVE +debt in current liabilities + long-term debt – deferred taxes and investment tax credit (preferred stock liquidating value was not quarterly available in Compustat)*. MB is the market-to-book value of assets. EBIT is calculated as *revenue – operating costs* and EBIT/TA is EBIT divided by total assets. D&A/TA is the depreciation and amortization divided by total assets. Ln(TA) is the natural log of total assets. FA/TA is the fixed assets, calculated as property, plant, and equipment, divided by total assets. R&D/TA is the research and development costs divided by total assets.

	Mean	SD	Median	Min.	Max.	Skew	Kurtosis
TDA	1.51	40.16	0.09	0	5319	86.75	9301
TDM	0.14	0.26	0.04	-32.94	1.71	-39.11	5209
MB	28.63	620	1.85	-0.66	62710	56.06	4118
EBIT/TA	-0.7	441.04	0	-9017	44.33	-199.79	43416
D&A/TA	0.02	0.14	0.01	-0.01	18.24	93.08	10324
Ln(TA)	3.12	2.37	3.07	-6.91	12.32	-0.08	1.23
FA/TA	0.49	1.08	0.33	0	102	42.22	2931
R&D/TA	0.28	38.2	0.02	-6.92	8825	229.41	52976