Acknowledgments

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We take full responsibility for the content of this thesis.

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Abstract

In this master's thesis we have examined which factors are important for explaining and predicting capital structure. The study examines American firms listed on the New York Stock Exchange during the period from 1980 to 2019. To gain a better understanding of capital structure decisions and robustness in our analysis, we have used both market and book values in the calculation of leverage. The list of possible explanatory variables comes mainly from M. Frank and V. Goyal (2009), but with some differences. Economic theories and literature on capital structure is applied for interpreting the effects of the variables selected.

The purpose of the study is to gain a better understanding of which factors influences financial decisions aimed at capital structure. To determine which of the variables that are important, we have used two different Least Absolute Shrinkage Selection Operator models, referred to as the normal and adaptive LASSO. After testing the variables selected by the normal LASSO and the adaptive LASSO for robustness, we were left with one model for book-based leverage, and two models for market-based leverage. The model for book-based leverage consists of the variables industry median leverage, cash holdings and Z-score. The normal LASSO models for market-based leverage selects the same variables, but adds market-to-book. The adaptive LASSO model also adds market-to-book, but excludes Z-score.

The core factors determined by M. Z. Frank and V. K. Goyal (2009) is used as a benchmark for comparison when evaluating our models' in-sample and out-of-sample performance. Our models are slightly better than the core model at explaining and predicting capital structure in our data, but only by small margins.

Abstract

I denne masterutredningen har vi undersøkt hvilke faktorer som er viktige for å forklare og predikere kapitalstruktur. Studien undersøker amerikanske firmaer notert på New York Stock Exchange i perioden 1980 til 2019. For å fange opp et bredere spekter angående beslutninger tilknyttet kapitalstruktur, samt robusthet i vår analyse har vi anvendt både bokførte og markedsverdier i beregningen av gjeldsgrad. Listen over mulige forklaringsvariabler er hovedsakelig basert på M. Z. Frank og Goyal (2009), med noen justeringer. Økonomisk teori og tidligere litteratur er lagt til grunn for tolkningen av de ulike variablene som er utvalgt av modellene våre.

I utvelgelsen av viktige variabler har vi anvendt to ulike Least Absolute Shrinkage Selection Operator-modeller, referert til som normal og adaptive LASSO. Etter å ha gjennomført robusthetstest for de ulike modellene sitter vi igjen med tre ulike modeller, en modell for bokført gjeldsgrad og to modeller for markedsbasert gjeldsgrad. Modellen for gjeldsgrad basert på bokførte verdier består av variablene industry median leverage, cash holdings og Z-score. Normal LASSO-modellene for gjeldsgrad basert på markedsverdier består av de samme variablene, men legger også til market-to-book. Den adaptive LASSO-modellen legger også til market-to-book, men ekskluderer Z-score.

Kjernefaktorene til M. Z. Frank og Goyal (2009) er brukt som sammenligningsgrunnlag for å evaluere våre modeller. Modellene våre presterer på generelt grunnlag litt bedre med tanke på forklaring og prediksjon av kapitalstruktur, men med marginale forskjeller.

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1.Introduction

Capital structure is a common research field in corporate finance. Capital structure describes how firms choose to finance their investment and operation through equity and debt. Why is capital structure important? When firms make important internal decisions, the financial structure of the firm is one of the key questions. What is the most effective composition debt and equity that maximizes the firms' value, and is sustainable in the long run? These are reasons for capital structure having become such a common, developed, and advanced research field. Although, capital structure has a rich history in corporate finance, the empirical findings have not been consistent, and not unambiguously supported by the different theories.

Miller and Modigliani (1958) developed two propositions, where they show that in perfect capital markets without taxes, the capital structure have no impact on the firms' total value. However, expected return on equity will increase when the firm issues debt. Although Miller and Modigliani (1958) showed a simplified but unrealistic reality, the theory became one of the first acknowledged literature on corporate finance. Therefore, violating the assumptions of Miller and Modigliani's theorem makes it possible to identify which factors may have an impact on companies' financing decisions. This is the basis for later research literature and theoretical contributions. The trade-off theory examines the benefits of debt in form of a tax shield and cost of financial distress (Myers, 1984). Furthermore, Myers and Majluf (1984) developed the pecking order theory, which is a signaling theory that focuses on how asymmetric information affects firms' financial decisions. Additionally, the market timing theory shows that financial decisions are based on the situations in the financial market (Baker & Wurgler, 2002).

1.1.Background and research question

The most common approach for explaining and predicting capital structure are linear models, where Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are methods applied for variable selection. However, linear models tend to raise several problems in the search for reliable and stable factors. Gomes and Schmid (2010) and Bhamra, Kuehn, and Strebulaev (2010) found that conventional linear models struggles with multicollinearity and overfitting. Tibshirani (1996) introduced the Least absolute shrinkage selection operator (LASSO), a regression method used for variable selections and generalization. LASSO shrinks the coefficients by introducing a penalty term to the OLS. The least important variables get coefficients set equal to zero, thus excluding them from the model. However, shrinkage of coefficients tends to produce biased estimates and unreliable results when a few assumptions gets violated. As a result Zou (2006) proposed the adaptive LASSO model. The adaptive LASSO model adds a weight vector to the penalty term, where each coefficient gets penalized different. The least important variables get assigned higher weights and are therefore more likely to get excluded from the model. Thus, the adaptive LASSO often selects more parsimonious models.

LASSO is a relatively unexplored method for researching capital structure, but it has been applied in some papers. Sohrabi and Movaghari (2019) examined reliable factors of capital structure in Iran using LASSO, and found that their model performed better than the core model presented by M. Frank and V. Goyal (2009). Amini, Elmore, and Strauss (2019) used different machine learning methods, including LASSO, to predict capital structure for US listed firms, where they found that LASSO performed relatively equal to normal linear models.

The basis of data consists of balance sheets, income statements and macroeconomic development. The data often varies in business circles, which often result in the variables being correlated. LASSO is a more robust method regarding multicollinearity and overfitting compared to conventional linear models. LASSO is a relatively unexplored method for developing capital structure models, and therefore an interesting approach for researching corporate leverage. For these reasons, we have applied the normal and the adaptive LASSO for trying to answer the following research question:

Which variables explain and predict capital structure – a LASSO approach

The research includes firms listed on New York Stock Exchange in the period from 1980 to 2019. The sample consist of 6 276 firms with 76 341 firm-year observations after excluded for missing values. The sources for our data is the Compustat database, the CRSP database, the Internal Revenue Service Data Book and the Federal Reserve Bank. The variable list is based on M. Z. Frank and V. K. Goyal (2009), however, following Amini et al. (2019), we have also included Z-score as proxy for probability of financial distress and Cash holdings as a proxy for liquidity. Additionally, firm beta is included as another proxy for risk.

When using panel data with a significant timeline and many firms with different characteristics, the stability of the explanatory factors, as well as the levels of leverage, have to be taken into consideration. DeAngelo and Roll (2015) showed that leverage highly fluctuates over time. Therefore, stable capital structure is only virtually temporary. Furthermore, in cases of changing leverage target, the capital structure stabilizes by the second year after the event (Cook, Fu, & Tang, 2016). On the other side, Lemmon, Roberts, and Zender (2008) found that capital structure remain stable over time and that variation to leverage is mainly driven by an unobserved time-invariant. Furthermore, they suggest that variation of capital structure is primarily determined by factors that remain stable over time, and that these findings are important to understand capital structure heterogeneity. To understand the heterogeneity in capital structure, the identification of robust independent variables is important. To test for robustness in our research, we divided our data into ten subsamples based on firm-specific characteristics, and ten random subsamples. Before presenting the final models, we cross-check the explanatory variables selected by LASSO for robustness across the firm specific subsamples and random subsamples.

When evaluating our results, we use the core model presented by M. Z. Frank and V. K. Goyal (2009) as a benchmark for comparing our models' performance for both in and out of sample. When evaluating the models in-sample, we focus on R-squared, AIC and BIC, while we use root mean square error and mean absolute error to measure the models' performance out-of-sample.

1.2.Structure

Section 2 introduces the theoretical framework for our study. Section 3 consists of earlier literature and empirical findings. Section 4 presents the dependent and independent variables used in the analysis. Section 5 presents data and descriptive statistics. Section 6 present the methods applied in our analysis. Section 7 presents empirical findings and economic interpretation of the selected variables. Section 8 sums up the empirical findings and concludes the research question. Section 9 points to some guidelines for further research.

2.Theory

2.1.Miller and Modigliani

Miller and Modigliani (1958) published “The cost of capital” which became the first established article within corporate finance, and became a foundation for published papers and later developed theories. Miller and Modigliani (1958) claim that under strict assumptions and perfect capital markets, the company’s total value will not be affected by capital structure. The article presents their main findings in two prepositions.

Proposition 1 states, the value of a company is the present value of the expected cash flows. In perfect capital markets, equity and debt are perfect substitutes. Therefore, companies with the same expected cash flows will have the same value regardless of the capital structure. In other words, the capital structure does not affect the value of the company.

Proposition 2 states that an increase in debt will increase the risk for the shareholders, and they will therefore have to be compensated by a higher expected return. Thus, expected return on equity will increase proportionally with the increased debt ratio. However, total expected return stays the unchanged, which means the total value of the company also stays unchanged.

For the propositions to hold, Miller and Modigliani (1958) assumes that any company in the same class must be priced equally, where companies within the same class have the same expected return and risk. If the proposition does not hold, arbitrage opportunities will occur, and investors could exploit the situation to gain a risk-free profit by buying and selling stocks and bonds with the same expected return to different prices. Although, as investors starts exploiting these arbitrage opportunities, the value of shares will move towards equilibrium and eliminate the arbitrage opportunity. For propositions 1 and 2 to hold, there cannot exist any market imperfections, such as asymmetric information, arbitrage opportunities, cost of financial distress, tax benefits of debt or transaction cost.

Miller and Modigliani (1958) got criticism for their unrealistic assumptions concerning capital structure and firm value. Asymmetric information, equal access to financial markets, taxes, transaction costs e.g. are present in financial markets, which violates the assumption of perfect capital markets. However, since there were no generally accepted theories of capital structure at the time, the Miller-Modigliani theorem influenced the early development of both the trade-off theory and the pecking order theory (Frank & Goyal, 2007).

2.2.Pecking order

The pecking order theory is a signaling theory developed by Myers and Majluf (1984), which claims that firms' choice of capital structure is governed by asymmetric information. In general, the theory states that when choosing between different financial sources, firms will prefer using internal funds over external funds, and debt over new equity. By using internal funds, the firm avoids flotation costs and do not have to reveal extra proprietary information, which can negatively affect the value of the firm and its market position. If external finance is required, firms will, according to the pecking order theory, issue the safest securities first. The firm issues debt, then hybrid securities, and new equity as the last resort (Myers, 1984).

The pecking order theory assumes that the managers has more information on the true value of the firm, in the form of current earnings and future opportunities, than external investors. Myers and Majluf (1984) assumes that the managers will act in the interest of the current shareholders and will therefore not issue new equity when their stock is undervalued. They will, however, prefer to issue new equity when its market value is higher than the real value. The investors realize this and will therefore not be willing to buy the new equity unless the price goes down or they get a discount. If the firm choose to issue new equity, the fall in stock prices should be offset by the net present value of the investment opportunity.

Debt has prior claim on assets and earnings. Debt holders are therefore less affected by errors in valuation of the firm. Additionally, a debt issue can signal to outside investors that the managers are confident in the firm's investments and ability to repay the debt (Hillier, Ross, Westerfield, Jaffe, & Jordan, 2016). The debt's interest can be viewed as an asymmetric information premium that reflects the firm's risk.

There have been several empirical studies on the pecking order theory published, with conflicting results. Shyam-Sunder and Myers (1999) found strong empirical result in support of the pecking order theory when they tested it against the static trade-off theory. Ghosh and Cai (1999) found more significant results for the pecking order theorem, but suggests that static trade off and pecking order are not mutually exclusive. Vasiliou, Eriotis, and Daskalakis (2009) found no statistically significant difference between the number of firms that preferred retained earnings and the firms that preferred debt and new equity when making financial decisions.

2.3. Trade-off theory

The static trade-off framework states, the optimal debt ratio is determined by a tradeoff between the benefits and cost of debt, where the marginal benefits equals the marginal cost (Myers, 1984). The benefits from debt comes in the form of a tax shield. An increase in debt increases the cost of interest, which in turn, reduces the taxable income. However, an increase in debt will also increase the cost of financial distress. The static framework assumes no costs of adjustment, so firms can move freely towards their target debt ratio. However, no adjustment cost is an unrealistic assumption. Therefore, firms cannot adjust to their target leverage immediately.

The dynamic trade-off theory is an extension of the static trade-off theory. It has a wider range of acceptable debt ratios, rather than a specific debt target, and uses a continuous-time framework rather than a single-period. The firms will rebalance their leverage if they move too far away from target. Fischer, Heinkel, and Zechner (1989) demonstrated the danger of viewing observed debt ratios as "optimal" and, therefore introduced firm-specific properties to avoid these problems. Fischer et al. (1989) concluded that firms that are smaller, riskier, has lower tax rate and has lower cost of financial distress exhibits wider swings in their leverage. However, they only accounted for one way of characterizing the benefits of debt and cost of financial distress.

Agency costs may also be included in the trade-off theory framework. Agency costs typically occur when managers make decisions which conflict with the interests of the firm, for example by investing in a new expensive office. According to Jensen (1986), issuing debt will reduce the managers options to exploit the free cashflow, hence reduce the agency cost. There also exist agency costs of debt, like when the manager invests in risky projects that is in the interest of the shareholders, but not the creditors.

2.4. Market timing

The market timing theory claims that there is no optimal capital structure, and firms choose between equity and debt based on the situation in the financial markets. Baker and Wurgler (2002) states that capital structure evolves as the cumulative outcome of past attempts to time the equity market. Firms prefer to issue equity when the market value is high compared to the book value and the historical market value. When the market value of the equity is low, firms tend to repurchase stock.

Baker and Wurgler (2002) found that firms with low gearing tends to have acquired capital when their market valuation where high. The firms that raised capital at low market value where more inclined to have high leverage. Further, they observe that fluctuations in market valuations have a significant and long-term effect on capital structure. They also found that firms tend to issue equity when investors are somewhat too optimistic about future earnings prospects. In a study by John R. Graham and Harvey (2001), they found that two-thirds of the asked CFOs agree that errors in valuation of equity plays an important part when considering issuing new equity or repurchasing stock. In a study by John R. Graham and Harvey (2001), they found that two-thirds of the asked CFOs agree that errors in valuation of equity plays an important part when considering issuing new equity or repurchasing stock.

3.Literature review

In this section we highlight a selection of empirical findings on capitals structure, followed by a review of two studies using LASSO as an approach for researching leverage.

3.1.Capital structure

M. Frank and V. Goyal (2009) studied which factors are reliably important for explain capital structure of American traded firms in the period from 1950 to 2003. They started with a long list of variables and used a stepwise process based on the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to select the most reliable ones. Their research resulted in six core factors to predict leverage. The factors selected were median industry leverage, tangibility, log of assets and expected inflation, which had positive effect on leverage, and market to book assets ratio and profit which had negative effect on market-based leverage. However, log of assets, market to book and expected inflation were not reliable for book-based leverage. A reasoning behind this is that the variables measures the expectations for the firms' future and is therefore not suited for explaining the backwards-looking book-based leverage. Their findings capture the following pattern of the data:

- When the median leverage in the industry is high, the competing firms tend to have high leverage.
- Firms with a high market-to-book ratio are more likely to have low leverage.
- Firms with tangible assets tend to have more leverage.
- Larger firms tend to have more leverage than smaller firms.
- Profitable firms tend to have lover levels of leverage.
- Firms tend to have high leverage when the expected inflation is high.

To determine which factors are important for explaining leverage, Harris and Raviv (1991) summarizes earlier hypothesizes and empirical findings of previous capital structure studies. Their research focused on agency cost, asymmetric information, market interactions and corporate control in the selection of variables. They concluded that size, assets, growth opportunities and non-debt related tax shield had a positive effect on leverage, while profitability, uniqueness, probability of financial distress, advertising expenses and research and development affected leverage negatively. Further, they highlight the importance of getting an overview over which determinants are important in different contexts.

J. Chen and Strange (2005) investigated the determinants of capital structure of firms in China. They found that leverage is negatively affected by profit, while firm size and risk have a positive relation with leverage, but only when the market value debt ratio is applied. The number of years a company is listed had a significant positive effect on the book value of leverage, but not a significant effect on the market value of the debt ratio. Further, their results indicated that growth and taxation were not important determinants. They also pointed out that a country's cultural and institutional properties need to be considered when explaining capital structure. Yang, Lee, Gu, and Lee (2010) concluded that stock return, expected growth, uniqueness, asset structure, profitability, and industry classification are the main explanatory factors of capital structure for Taiwanese firms. When studying capital structure of Canadian firms, Nunkoo and Boateng (2010) found that profitability and tangibility have a positive and significant impact on leverage, while growth opportunities and size have a negative impact on financial leverage.

Fama and French (2002) tested the predictions the trade-off and the pecking order theory made about dividend and leverage. They found that profitable firms had higher dividends payout, while firms that were investing a lot had lower payout. The dividend payout had a negative effect on leverage, supporting the pecking order theory. Their results indicate a negative relation between profitability and leverage. Thus, the assumptions associated with static trade off theory does not hold. They also found concerns associated with the pecking order theory, where small firms with high growth tends to issue significant amounts of equity.

In a study on the stability of capital structure, DeAngelo and Roll (2015) show that firms' leverage does not remain stable over time. Many firms have high and low leverage at different times, and firms seldom have a leverage ratio over 0.5 consistently over time. When stability of leverage does occur, it is mainly at firms with low leverage, and it is almost always temporary. Since leverage varies so widely, they argue that it is more likely that the factors determining leverage does not adhere to a specific debt/equity ratio. They conclude that theoretical theories on capital structure needs to account for a target leverage ratio that allows wide time-series variation. On the other side, Lemmon et al. (2008) found that corporate capital structure is stable over time, and that variation leverage is driven by an unobserved time-invariant effect. They found that high and low leveraged firms tend to remain stable for about two decades, which are largely unexplained by other research of capital structure determinants. This stability is also observed at firms prior to their initial public offering and after delisting, indicating that capital structure is primarily determined by factors that remain stable over long periods of time. Cook et al. (2016) investigated the impact of corporate asset restructuring in the US. They found that after restructuring, firms that downsized reduced their target leverage, while it increased for growing firms. Their result indicate that capital structure stabilizes after two year after restructuring, where downsizing firms tends to repurchase debt, and growing firms are more likely to issue debt.

J. R. Graham and Leary (2011) found that the predictors in capital structure appear to have nonlinear relations with the leverage measures, which is a relatively unexplored field in capital structure. Furthermore, Gomes and Schmid (2010) and Bhamra et al. (2010) showed that leverage and asset returns are related to growth, equity issuance cost and macroeconomic risk through complex interactions. Where linear models have been struggling with multicollinearity and overfitting, machine learning models can capture hidden interactions and therefore improve the forecasting accuracy.

3.2.Capital structure – LASSO approach

Sohrabi and Movaghari (2019) used LASSO, in combination with a stability selection approach, for determining the most important factors explaining capital structure in Iran, using the period from 2006 to 2018. Their results corresponded somewhat with the core factors selected by M. Z. Frank and V. K. Goyal (2009), but with some differences. For market-based leverage the variables median industry leverage, market-to-book ratio, and profitability were consistent with M. Frank and V. Goyal (2009), but firm size and tangibility were excluded. Additionally, liquidity was included as a stable factor, where it had a negative effect on leverage. For book-based leverage, firm size and market-to-book ratio were not selected as reliable important factors. Tangibility was selected, but it did not meet their requirements for being a stable factor. They compared their model to the core factors selected by M. Z. Frank and V. K. Goyal (2009) and found that it produced better estimates, both in-sample and out-of-sample.

Amini et al. (2019) used several machine learning techniques, including LASSO, for predicting capital structure for listed firms in the US. The variables selected by LASSO were industry median leverage, cash holdings, profitability, growth in GDP, market-to-book, stock returns, and Z-score, where industry median leverage and cash holdings were the most important variables. When comparing the predictive performance of their models, they focused on root mean square error and out-of-sample R-squared while using the core model presented by M. Frank and V. Goyal (2009) as a benchmark. The LASSO model performed relatively similar to the core factors, but were outperformed by other non-linear machine learning techniques, such as random forest and neural networks.

4.Variable presentation

In this section we present the dependent and independent variables. A more detailed description is listed in table 7.

4.1.Dependent variables

Empirical studies of capital structure have many definitions on leverage, where the most common leverage measure is the ratio of total debt to market value of assets (TDM) (Amini et al., 2019). John R. Graham and Harvey (2001) reported that when deciding on capital structure, managers focus on book values. Additionally, Fama and French (2002) argued that since the market value of equity strongly fluctuates and is affected by a number of external factors, the leverage using book values better reflect the firm's targeted debt ratio. A downside with using book values however, is that the firm's actual financial condition will not be accurately represented (Bessler, Drobetz, & Kazemieh, 2011). Leverage based on book values measures what has taken place, while leverage based on market value measures the expectations for the future. Thus, TDA is backwards looking, while TDM is forward looking (M. Z. Frank & V. K. Goyal, 2009). To get a broader understanding of the determinants of capital structure, we apply both TDA and TDM as dependent variables in our study.

4.2.Independent variables

Our sample of variables closely follows M. Z. Frank and V. K. Goyal (2009), but like Amini et al. (2019), we have included cash holdings and unlevered Z-score. However, we have excluded net operating loss carryforward due to a high percentage of missing observations and regulated dummy. Furthermore, the independent variables are divided into three panels: firm characteristics, industry characteristics and macro characteristics.

The firm specific factors we have included are profitability, firm size, growth, nature of assets, risk, taxes, supply side factors and stock market conditions. Firm size is proxied by the logarithm of total assets and a maturity dummy which equals one if the firms have been listed for five years or more. Growth is proxied by the market-to-book ratio, the change in logarithm of assets and capital expenditure. Nature of assets is proxied by the tangibility of assets, research and development investments, non-production cost, cash holdings which represents liquidity and whether a firm is in an industry that produces unique products or not. Taxes are proxied by the top statutory tax-rate, the non-debt tax-shield from depreciations and investment tax credit. The proxies we have included for risk is the variance of asset returns, the stock return beta, and unlevered Z-score. Z-score presented by Altman (1968) is a formula which evaluates a public firm's likelihood of bankruptcy. The model takes a weighted combination of reported profitability, liquidity, solvency, and activity ratios into account to predict the probability of a firm going insolvent. We use the unlevered Z-score since that it is not affected by capital structure decisions. A higher Z-score indicates a lower risk of bankruptcy. Credit rating from the Compustat database is used as a proxy for the supply-side factors. The proxies for the stock market conditions are the cumulative annual stock returns and market returns. We have also included a dummy for whether a firm pays dividend or not.

The industry-level characteristics are proxied by the yearly median of industry leverage and the median of asset growth of each industry. The macro-level characteristics that are included are the debt market conditions and the macroeconomic conditions. Term spread, calculated by the difference between the 10-year bond returns and the 1-year bond returns, are used as a proxy for the debt market conditions. The proxies for the macroeconomic conditions are expected inflation, the growth of annual corporate profits, and the growth of real gross domestic product.

5.Data

In this section present the data basis for the analysis, followed by a presentation of descriptive statistic, correlations with associated comments to variable tests.

5.1.Data

The sample consist of U.S. firms listed on New York Stock Exchange for the period from 1980 to 2019. Our data consists of accounting and balance sheet data from the Compustat database, stock and market returns from the Center for Research in Security Prices (CRSP) database. Furthermore, we use the Internal Revenue Service Data Book for tax rates, the Compustat database for the standard and poor's issuer credit ratings and the Federal Reserve Bank for inflation, corporate profits, and GDP. The variables used in different regressions and analysis are winsorized at the 0,5% level in both tails of the distribution to reduce outliers. To avoid errors in the leverage measures, observations of total assets with negative or missing values are excluded from the data. All explanatory variables used in the analysis are lagged by one year. After cleaning the dataset for missing values and excluding financial and utility firms, we are left with 6276 firms and 76341 firm-year observations.

5.2.Descriptive statistics

Table 1. Descriptive statistics

This table provides descriptive statistics of dependent and independent variables. Panel A provides firm level characteristics, panel B industry level characteristics and panel C macro level characteristics. For each variable, the number of observations, mean, median, standard deviation, min- and max values are reported.

Variable	Observations	Mean	Median	SD	Min	Max
			Panel A: Firm-Level Characteristics			
Leverage Measures						
TDM	76341	.2767957	.2252257	.236965	0	.9855053
TDA	76341	.2638742	.2440552	.1971466	0	.9995311
Profitability:						
Profit	76072	.102904	.1240249	.1724267	-1.068912	.5752287
Firm size:						
Assets	76341	6.187635	6.177896	2.253481	1.009052	12.37558
Mature	76341	.8075739	1	.3942085	0	1
Growth:						
Mktbk	76341	1.481256	1.051765	1.467136	.109086	13.26957
ChgAsset	70442	.0832259	.0544591	.291266	-1.901351	2.344024
Capex	75413	.0684021	.0464987	.0755412	0	.7127895
Nature of Assets:						
Tang	76178	.3329697	.2777747	.2396938	0	.9606832
RnD	76341	.0628609	0	.3978591	0	4.448529
Unique	76341	.2490929	0	.4324905	0	1
SGA	69516	.2714443	.1907744	.4628983	.0091769	5.244821
Cash	76333	.1234983	.0641232	.1613255	0	.9957687

Variable	Observations	Mean	Median	SD	Min	Max
Taxes:						
TaxRate	76341	.3661794	.35	.0509212	.21	.46
Depr	74854	.049374	.0417981	.0359469	0	.2598774
InvTaxCr	75555	.0002281	0	.0026168	0	.0567601
Risk:						
StockVar	74351	.0028848	.0007194	.0269102	2.92e-06	.6644924
Z-Score	72066	1.571359	1.883543	2.4504	-16.49438	6.109081
Beta	69864	.7640345	.7229823	.4926329	-.50378	2.33129
Supply-Side Factors:						
Rating	76341	.1999581	0	.3999712	0	1
Stock Market Conditions:						
StockRet	74915	.0803265	.004362	.5545947	-.865285	3.333333
CrspRet	76341	.0916475	.1039917	.1557926	-.384858	.3411067
Dividend:						
Dividend	76341	.5563459	1	.4968183	0	1
Panel B: Industry-Level Characteristics:						
Industry:						
IndustLev	76341	.2523533	.2467205	.1280152	0	.9379858
Industgr	75593	.0640675	.0575082	.1022538	-.281124	.5385156
Panel C: Macro-Level Characteristics:						
Debt Market Conditions:						
TermSprd	76341	.0130957	.0122312	.0101851	-.0087454	.0311976
Macroeconomic Conditions:						
Inflation	76341	.0367158	.0297271	.0201626	.0115828	.120835
MacroProf	76341	.0502398	.0574575	.1331091	-.2276915	.3111899
MacroGr	76341	.0266015	.0282104	.0177852	-.0256949	.0698677

Firms in our sample has an average market-based debt ratio of 27.7% and an average book-based debt ratio of 26.4%.There are large variations in the debt ratios, but we observe from the standard deviations that the majority of the firms does not have leverage ratios over 50 percent. Profit rate are on average 10.3%, however, profit has a standard deviation of 0.172, which means it fluctuates a lot. The natural logarithm of total assets has an average of 6.1. The number of mature firms that have been listed for five years or more make up for 81% of our firm-year observations. The growth variable market to book has an average of 1.48, which indicates that firms on average has a market value 48 percent higher than their book value. Assets growth and capital expenditures has averages of 8.3% and 6.8%. Asset growth, however, display a standard deviation of 0.29, indicating that there is a large variation for each firm. Assets tangibility, research and development, uniqueness, non-production cost and cash holdings has an average of 33.3%, 6.3%, 24.9%, 27.1% and 12.4%, respectively. The average top tax rate is 36.6%, deprecation and investment tax credit have an average of 4.9% and 0.02%. Average daily stock variance equals 0.29%, but the variable has a comparatively large standard deviation of 0.027. Z-score has an average of 1.57. The Beta has a mean of 0.76 and a standard deviation of 0.49. The average credit rating is 0.20, which means that 20 percent of our firm-year observations have credit rating of BB or better. The cumulative annual stock return average equals 8.03%, while the annual average market return equals 9.2%. The number of firms paying dividend make up 55.5% of the firm-year observations in our data. In panel B, industry median leverage and industry growth have an average of 25.2% and 6.4%. In panel C, term spread describes the difference between 10-year bond and 1-year bond, with an average through the period equal to 1.31%. The macroeconomic conditions variables inflation, macro profit growth and growth in GDP has an average of 3.67%, 5.02% and 2.66%.

5.3 Correlations

Table 2. Correlation matrix

The table present pairwise correlations coefficients between the leverage measures and the control variables. The correlations coefficients presented in the table are the coefficients for the whole sample period. We have broken the sample period up into four decades, where the first sign indicates correlation in the first decade, second sign the second decade, third sign third decade and the last sign for the last decade. + indicates positive and significant correlation within the decade or period, - indicates negative and significant correlation, and. indicates no significant correlation. So [++++] indicates positive and significant correlations through the entire sample, [--++] indicates negative and significant correlations in the two first decades and positive and significant correlation in the third decade and the last period, for example. Significance level is defined at the 5 percent level.

Variable	TDM	TDA	Variable	TDM	TDA
Profit	-0.0331*** [--++]	0.0107*** [--++]	StockVar	0.0284*** [++++]	0.0200*** [+++.]
Assets	0.1486*** [++++]	0.1658*** [++++]	Z-score	-0.0278*** [--+.]	-0.1036*** [---.]
Mature	0.0406*** [+++.]	-0.0240*** [--..]	Beta	-0.0202*** [---+]	0.0181*** [+--+]
Mktbk	-0.4206*** [----]	-0.1804*** [----]	Rating	-0.0277*** [-..-]	0.0412*** [.+++]
ChgAssets	-0.0792*** [----]	0.0004 [..-.]	StockRet	-0.1425*** [----]	-0.0487*** [----]
Capex	0.0069* [--.+]	0.0715*** [++++]	CrspRet	-0.0571*** [.---]	0.0036 [+.--]
Tang	0.2354*** [++++]	0.2327*** [++++]	Dividend	-0.0406*** [--.-]	-0.0380*** [--++]
RnD	-0.1341*** [----]	-0.1009*** [----]	IndustLev	0.4737*** [++++]	0.5209*** [++++]
Unique	-0.0938*** [----]	-0.1113*** [----]	IndustGr	-0.1038*** [----]	-0.0287*** [----]
SGA	-0.1712*** [----]	-0.1149*** [----]	TermSprd	-0.0438*** [--+-]	-0.0266*** [.-.-]
Cash	-0.3856*** [----]	-0.3683*** [----]	Inflation	0.0798*** [++-+]	-0.0060* [--.+]
TaxRate	0.0447*** [.-.-]	-0.0338*** [-..-]	MacroProf	-0.0660*** [.---]	-0.0480*** [----]
Depr	0.0826*** [++++]	0.1275*** [++++]	MacroGr	-0.0237*** [---+]	0.0179*** [.+.+]
InvTaxCr	0.0241*** [+.+.]	-0.0051 [-+++]			

*** p<0.01, ** p<0.05, * p<0.1

Table 2 displays the pairwise correlation between the dependent and independent variables. The table shows which variables that have significant correlation with the market-based and book-based leverage. Additionally, the table shows if the correlation is significant positive or negative at the five percent level for the different decades.

For market-based leverage, we mostly find significant correlations for every period, but with some exceptions. Assets, tangibility, depreciation, stock variance and industry median leverage have significant positive correlation with market-based leverage for every period. Market-to-book, change in assets, research and development, uniqueness, SGA, cash holdings, stock returns and industry growth display significant negative correlation with market-based leverage for all the periods. The variables profit, beta, term spread, inflation and growth in GDP have significant correlation with market-based leverage, but the sign of the correlation varies over the periods.

The variables that have significant positive correlation for all the periods with book-based leverage are assets, capital expenditures, depreciation, and industry median leverage. On the other side, we observe significant negative correlation for all the periods for the variables market-to-book, research and development, uniqueness, cash holdings, stock returns, industry growth and macro profit growth. Profit, investment tax credit, beta and dividend have significant correlation with book-based leverage, but the correlation varies between negative and positive.

We observe moderate correlation with market-based leverage for market-to-book which has a coefficient of -0.42, cash holdings with a coefficient of -0.39 and industry median leverage with a coefficient of 0.47. Book-based leverage has moderate correlation with the variables cash holdings, which has a coefficient of -0.37 and industry median leverage, with a coefficient of 0.52. The rest of the variables display low or negligible correlation with market-based and book-based leverage.

5.4 Statistical tests

Test for the different assumptions regarding OLS are presented in Appendix 3 . The VIF-index indicates no issues relative to multicollinearity in our data set (see Table 18). Table 19 shows the White-test which indicates significant heteroskedasticity. The results from the Wooldrigde test in Table 20, indicates significant autocorrelation of the first order in our data. To account for these problems, we utilize clustered standard errors. The result in Table 20 indicates significant skewness and kurtosis in the test for normality. To reduce the variance in the residuals, the dataset is winsorized at the 0.5 level in both tail of the distribution. Furthermore, to make sure the data doesn´t consist of irregularities have we compared the descriptive statistics to our benchmark M. Z. Frank and V. K. Goyal (2009). Before moving on to the analysis have we compared the descriptive statistics with Amini et al. (2019) to get a more updated comparison, the comparison indicates no issues regarding the data.

6.Methodology

In this section we present Ordinary least squared (OLS), in-sample and out-of-sample model validation, followed by a more thorough presentation of Least absolute shrinkage selection operator (LASSO) and a review of model robustness.

6.1.Ordinary least squared

OLS is a method for estimating parameters in a linear regression. The coefficients estimated by OLS minimize the sum of the squared residuals. For OLS to produce the best and valid coefficient, seven assumptions need to be fulfilled (se appendix OLS). When evaluating the performance of each model in-sample, we apply the R-squared, which measures the proportion of variance of the dependent variable explained by the model. Common methods for variable selection for normal linear models are the information criterions AIC and BIC. When selecting the model, choose the one with the lowest AIC or BIC measurement. BIC is asymptotically consistent, meaning the probability of BIC selecting the true model approaches one when the sample size increase to infinity. Further, BIC assumes that the amount of information that the sample provides depends only on the size of the sample. In other words, one observation is as good as another (Weakliem, 1999). R-squared, AIC and BIC are defined as:

$$R^2 = 1 - \frac{RSS}{TSS} \tag{1}$$

$$BIC = -2 * \log(Likelihood) + P * \log(N) \tag{2}$$

$$AIC = -2 * \log(Likelihood) + 2P \tag{3}$$

Where,

$P = number\ of\ paremeters$

$N = number\ of\ observations\ in\ the\ fitted\ model$

Common measure for evaluating the model's performance out-of-sample are the measures root mean squared error (RMSE) and mean absolute error (MAE). MAE measures how close the predictions are to the actual outcome, while RMSE measures the standard deviation of the differences between the predicted and observed values (Adetiloye & Awasthi, 2017).

RMSE represents the standard deviation of the residuals of the model, in other words it can be interpreted as standard deviation of the model's variance. Thus, we get a measure of how the estimates are spread and concentrated around the actual observed outcome. The RMSE is measured on the same scale as the dependent variable, and defined as:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\hat{y}_t - y_t)^2} \tag{4}$$

MAE measures the average absolute value of the residuals. Like RMSE, it is measured on the same scale as the dependent variable. However, whereas RMSE punishes larger deviations by quadrating the residuals, MAE does not differentiate between large and small values. MAE is defined as:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|\hat{y}_t - y_t| \tag{5}$$

6.2.Least absolute shrinkage selection operator

Least absolute shrinkage selection operator (LASSO) is a regression method used for variable selection and generalization popularized by Tibshirani (1996). LASSO combines properties from ridge regression and sub-set selection, making the model able to perform both variable shrinkage and selection. LASSO minimizes the sum of the squared residuals subject to a penalty term, where lambda is a tuning parameter that controls the amount of shrinkage of the coefficients (Nazemi & Fabozzi, 2018). As lambda increases, the coefficients continuously shrink towards zero. If lambda is equal to zero, then LASSO provides the same coefficients as OLS. The penalty term is lambda times the sum of the absolute value of the coefficients. This way, large coefficients increases the penalty term, and LASSO will therefore shrink them.

The LASSO is defined as:

$$\hat{\beta} = \arg\min \left[y_i - \sum_{j=1}^{p} x_j \beta_j \right]^2 + \lambda \sum_{j=1}^{p} |\beta_j| \tag{6}$$

Where,

$Y = Dependent\ variable$

$X = Independent\ variable$

$P = Number\ of\ independent\ variables$

$N = Number\ of\ observations$

$\lambda \geq 0$

LASSO replaces the penalty term ℓ_1 (2) in ridge regression with (3). The squared slope in the ridge regression makes it so that the coefficients can only be asymptotically close to zero, whereas the absolute value of the slope in the ℓ_1 parameter makes LASSO able to set coefficients equal to zero. Thus, LASSO can exclude redundant variables from the model.

$$P_\lambda(\beta) = \lambda \sum_{j=1}^{p} \beta_j^2 \tag{7}$$

$$P_\lambda(\beta) = \lambda \sum_{j=1}^{p} |\beta_j| \tag{8}$$

The estimates from OLS can often be unreliable. They usually have low bias, but suffer from large variance, which hurts the prediction accuracy. By shrinking the coefficients or setting some of them equal to zero, we trade higher bias for lower variance, but the prediction accuracy gets improved. Although, the shrinking of coefficients lead to more stable coefficients, small coefficients can be wrongly omitted (StataCorp, 2019, p. 7). Interpretation can also be a problem with OLS, which means it can be troublesome with many predictors to determine which variables have the most significant effect. According to Rapach, Strauss, and Zhou (2013), the LASSO method is more robust than other variable selection approaches, such as backward or forward stepwise regression. However, a shortcoming with LASSO is that it has a tendency to select a single independent variable from a group of highly correlated variables, but it avoids multicollinearity in the model (Rapach et al., 2013).

As previously mentioned, LASSO regression enjoys favorable properties from the stable ridge regression and variable selection from the subset selection. However, a good procedure should, besides continuous shrinkage, have the oracle properties. If an oracle were assisting in selecting the variables, then all the non-zero determinants would be included in the true model (Fan & Peng, 2003). A model has oracle properties if it identifies the right subset model $\{ j : \hat{\beta}_j \neq 0 \} =$ A, and has the optimal estimation rate, $\sqrt{n}\big(\hat{\beta}(\delta)_A - \beta_A^*\big) \underset{d}{\rightarrow} N(0, \Sigma^*)$, where Σ^* is the covariance matrix knowing the true subset model. Hence, the model performs as well as if the true underlying model were known in advance (Zou, 2006). Fan and Li (2001) found that the because the penalty term is singular in its origin, LASSO can perform automatic variable selection. However, the shrinkage of large coefficients tends to produce biased estimates, which can make the results unreliable. Thus, they conjectured that the oracle properties for LASSO does not hold. These results are supported by Zou (2006), and as a result proposed the adaptive LASSO. The adaptive LASSO defined as:

$$\hat{\beta}^{*(n)} = \arg\min \left[y - \sum_{j=1}^{p} x_j \beta_j \right]^2 + \lambda_n \sum_{j=1}^{p} \hat{w}_j \left| \beta_j \right| \tag{9}$$

Where

$\hat{w} = \frac{1}{|\beta|^{\gamma}}$ and $\gamma > 0$

Adaptive LASSO selects λ across multiple LASSO regressions with cross-validation. Variables with zero coefficients are removed after each cross-validation. Furthermore, the remaining variables are given penalty weights designed to drive small coefficients to zero. A higher beta leads to a lower penalty weight, while a lower beta leads to a higher penalty weight. Therefore, adaptive LASSO often results in a more parsimonious model with fewer variables. The adaptive weighted coefficients in the penalty term makes the adaptive LASSO produce consistent estimates which enjoys oracle properties, and the shrinkage of the coefficients leads to a near-minimax-optimal estimator (Zou, 2006). As we have two different LASSO methods, we refer to the LASSO originally presented by Tibshirani (1996) as the normal LASSO, while the LASSO presented by Zou (2006) is simply called the Adaptive LASSO.

6.3.Cross-validation

Cross-validation is a data resampling method, and a way lambda can be chosen. Cross-validation compares different values of lambda and selects the one that produces the lowest cross validation mean prediction error. By using k-folds cross-validation, the data is split into k different samples where one is used as a validation dataset, and the remaining sets are used as training. The training sets are then used to test different compositions of the parameters to fit the model and tested up against the validation dataset to calculate the prediction error. The process is then repeated k times, each with a different validation set (Chollet & Allaire, 2018, p. 79). However, when using k-fold cross validation on time series and panel data, we risk using future observations as training to predict past observations. We therefore use a rolling origin validation method presented by Bergmeir and Benítez (2012), which takes the historical development of the data into account, so that no future observations may be used to construct the forecasting model. Hence, the data is divided into time series consisting of individual validation sets and corresponding training sets. The training sets only contain historical observations that has occurred before the observations in the validation sets. There are two methods for rolling the training period forward: expanding and fixed window. Expanding window adds a period to the testing set each time it gets rolled forward. Fixed window does the same, but discards the first period of the training set for each step it gets rolled forward.

Expanding

Years \ Folds	1	2	3	4	5
1	*T*	*T*	*T*	*T*	*T*
2	*T*	*T*	*T*	*T*	*T*
3	*T*	*T*	*T*	*T*	*T*
4	*V*	*T*	*T*	*T*	*T*
5	.	*V*	*T*	*T*	*T*
6	.	.	*V*	*T*	*T*
7	.	.	.	*V*	*T*
8	.	.	.	.	*V*

Fixed

Years \ Folds	1	2	3	4	5
1	*T*	.	.	.	.
2	*T*	*T*	.	.	.
3	*T*	*T*	*T*	.	.
4	*V*	*T*	*T*	*T*	.
5	.	*V*	*T*	*T*	*T*
6	.	.	*V*	*T*	*T*
7	.	.	.	*V*	*T*
8	.	.	.	.	*V*

Figure 1 Illustration rolling origin validation method using expanding and fixed window.

The data is divided into training set and validation. A rule-of-thumb is that the validation period 20 percent of the data. 80 percent of the data is then used to forecast the first period after the training sets. Next, the training set is rolled forward to also contain the first validation set, and so on. Our training data is always before our testing data. But we can still have multiple trials just by rolling our data forward. We use a fixed window, as illustrated above, which lets the model evolve over time and the variables selected more robust (Swanson, 1998). For the sake of parsimony, we apply the "one-standard-error" rule where the lambda selected is within one standard error of the cross validation mean prediction error (Hastie, Tibshirani, & Freidman, 2009).

6.4.Robustness

For datasets that runs over a significant timeline, problems regarding stability for the control factors can occur. Myers (2003) states that theories on capital structure are conditional, and not general. This means that the characteristics of the firms play an important part in how well the theories perform. The data is therefore divided into ten firm specific subsamples: small, medium, and large firms, firms with low, medium and large growth, firms in high tech industries or not, and firms who were going through a refinancing of their capital structure or not (see table: subsamples). Meinshausen and Bühlmann (2010) proposed that subsampling would make a more stable variable selection. Therefore, as M. Frank and V. Goyal (2009), we divide our data into ten random subsamples. To ensure robustness, LASSO is run on the whole sample, the firm-specific samples, and the random subsamples. Additionally, we run LASSO on all the random subsamples within each firm-specific subsample. Only the variables that are included in at least 60 percent of the total LASSO regressions are included in the final model.

7.Empirical findings

In this section we present the finale models as a result from the robustness test. Thereafter, analysis of the in-sample models regarding model fit and BIC, followed by a variable discussion. Final, look at the out-of-sample prediction for the models.

7.1.Robustness tests

To ensure that the selected variables from LASSO are stable, we performed a robustness test before presenting the final models (see table 3). We observe that the normal LASSO more often includes variables that are not robust across the subsamples compared to the adaptive LASSO. Thus, the adaptive LASSO is more consistent in the selection of variables.

Table 3. Robustness test

This table reports the robustness for the variables selected by the normal LASSO and the adaptive LASSO for market-based and book-based leverage. The numbers highlighted in bold are the variables that were included more than 60 percent when running LASSO on the firm-specific subsamples and the random subsamples.

	TDM Normal LASSO	TDM Adaptive LASSO	TDA Normal LASSO	TDA Adaptive LASSO
IndustLev	**99.17 %**	**95.87 %**	**100.00 %**	**98.35 %**
Cash	**80.17 %**	**67.77 %**	**86.78 %**	**76.86 %**
Mktbk	**79.34 %**	**74.38 %**	18.18 %	6.61 %
Z-score	**61.16 %**	54.55 %	**83.47 %**	**79.34 %**
Profit	25.62 %	7.44 %	4.13 %	3.31 %
Dividend	22.31 %	14.05 %	28.93 %	17.36 %
Rating	15.70%	12.40%	17.36%	13.22%
Assets	9.09 %	5.79 %	21.49 %	13.22 %
StockRet	8.26%	5.79%	9.09%	8.26%
SGA	8.26 %	4.96 %	14.05 %	9.92 %
Tang	8.26 %	4.13 %	11.57 %	3.31 %
Unique	5.79 %	2.48 %	10.74 %	3.31 %
ChgAssets	4.13 %	1.65 %	13.22 %	4.13 %
TermSprd	3.31 %	0.83 %	4.13 %	0.00 %
StockVar	3.31 %	0.00 %	2.48 %	0.00 %
Inflation	3.31 %	3.31 %	4.96 %	5.79 %
Mature	3.31 %	0.83 %	10.74 %	3.31 %
Beta	2.48 %	0.00 %	2.48 %	0.83 %
RnD	2.48 %	0.83 %	4.13 %	0.83 %
Capex	2.48 %	0.83 %	3.31 %	1.65 %
Depr	1.65 %	0.83 %	4.96 %	1.65 %
CrspRet	1.65 %	1.65 %	2.48 %	2.48 %
InvTaxcr	1.65 %	0.83 %	0.00 %	0.83 %
TaxRate	0.83 %	0.83 %	3.31 %	0.83 %
MacroProf	0.83 %	0.00 %	0.00 %	0.00 %
MacroGr	0.00 %	0.00 %	1.65 %	0.00 %
IndustGr	0.00 %	0.00 %	0.83 %	0.00 %

The normal LASSO model for book-based leverage originally selected industry median leverage, cash holdings, Z-score, market-to-book ratio, change in assets, assets, and dividend as important factors for explaining capital structure. The adaptive LASSO had similar results but excluded market-to-book ratio and change in assets, indicating that growth may not be an important factor for explaining book leverage. After running the robustness test, we were left with the three variables industry median leverage, cash holdings and Z-score for both the normal and adaptive LASSO model.

The original variables selected by the normal LASSO for market-based leverage were industry leverage median, market-to-book ratio, cash holdings and Z-score, while Z-score was not included in the adaptive LASSO model. From the robustness test, we see that all these variables were included in the final models. Had we lowered the cut-off point to 50 percent, Z-score would also have been included in the adaptive model. However, we decided against this to see how the exclusion of Z-score would affect the results.

7.2.In-sample analysis

In this section we will present our findings for the normal and adaptive LASSO and compare the results with the core factor model. The results of our regressions for the normal LASSO is presented in table 4 and 5, the adaptive LASSO model in table 6, while the core factor model in table 10 and 11.

Table 4. Normal LASSO TDA

This table reports regression estimates using the variables selected by the normal LASSO, where the ratio of total debt to book value of assets (TDA) is used as the dependent variable. All the control variables used in the linear regression are lagged by one year, the variables are defined in appendix 1. The variables displayed in the table are selected by the linear LASSO regression. The table includes the regression coefficients with significant levels, clustered standard errors in parenthesis and T-values. Column 1-4 displays regressions results within each decade, and column 5 results for the whole sample. At the bottom rows, the number of observations, R-squared, RMSE, AIC and BIC are listed.

VARIABLES	(1) 1980-1989	(2) 1990-1999	(3) 2000-2009	(4) 2010-2019	(5) All Years
TDA					
IndustLev	0.578***	0.551***	0.602***	0.622***	0.601***
	(24.44)	(23.64)	(26.08)	(25.16)	(42.08)
Cash	-0.323***	-0.381***	-0.288***	-0.291***	-0.325***
	(-18.12)	(-24.80)	(-18.91)	(-15.61)	(-32.17)
Z-score	-0.0339***	-0.0220***	-0.0115***	-0.00853***	-0.0149***
	(-11.85)	(-12.58)	(-10.36)	(-6.333)	(-16.92)
Constant	0.233***	0.206***	0.153***	0.163***	0.175***
	(20.17)	(24.33)	(21.16)	(19.59)	(35.86)
Observations	16,417	18,638	16,738	13,804	65,597
R-squared	0.305	0.278	0.292	0.329	0.291
AIC	-15900.88	-14626.86	-13947.37	-10741.24	-54072.78
BIC	-15870.06	-14595.53	-13916.47	-10711.11	-54036.41

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

After the stability correction for the control variables, the final model for book leverage were equal for normal and adaptive LASSO, therefore the presented result will represent both. The final model includes the variables, median industry leverage, cash holdings, and Z-score, where median industry leverage is the only selected determinant of the core factors. Furthermore, all the variables are statically significant across all the periods for LASSO, while market-to-book and inflation are not significant for the core model in the period from 2010 to 2019 (see table 10**)**. The LASSO model for all the years have a R-squared of .291, where it remains relatively stable across the decades, and a BIC of -54 036.41. The R-squared from the original core factors is 0.257 and the BIC is -50 333.56 (see table 10). Compared to the core model, the LASSO model scores better on all the performance measures and is a more parsimonious model. Thus, based on the BIC approach, the LASSO model is preferred over the core model for book-based leverage. Table 12 of the standardized beta coefficients shows that the hierarchy of the most impactful variables on the book-based leverage is rather fixed, where industry median leverage reliably has the greatest effect throughout all the regressions. Z-score is the second most impactful variable in the period 1980-1989, but sees a steady decline after this, while cash holdings remain relatively stable.

Table 5. Normal LASSO TDM

This table reports regression estimates using the variables selected by the normal LASSO, where the ratio of total debt to market value of assets (TDM) is used as the dependent variable. The variables are selected by using the period from 1980 to 2005 as training and rolled forward to 2015, where the variables that produce the lowest cv mean prediction error are selected. Further, the "one standard error rule" is applied to get a more parsimonious model. All the control variables used in the linear regression are lagged by one year, the variables are defined in appendix Q. The variables displayed in the table are selected by the linear LASSO regression. The table includes the regression coefficients with significant levels, clustered standard errors in parenthesis and T-values. Column 1-4 displays regressions results within each decade, and column 5 results for the whole sample. At the bottom rows, the number of observations, R-squared, AIC and BIC are listed.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	1980-1989	1990-1999	2000-2009	2010-2019	All Years
TDM					
IndustLev	0.640***	0.549***	0.644***	0.581***	0.608***
	(23.68)	(21.42)	(24.89)	(21.94)	(38.44)
Cash	-0.339***	-0.300***	-0.250***	-0.253***	-0.287***
	(-16.33)	(-18.85)	(-16.64)	(-14.13)	(-27.68)
Mktbk	-0.0596***	-0.0484***	-0.0359***	-0.0408***	-0.0445***
	(-18.90)	(-23.15)	(-19.46)	(-15.03)	(-31.81)
Z-score	-0.0380***	-0.0241***	-0.0138***	-0.0121***	-0.0174***
	(-12.70)	(-14.80)	(-11.69)	(-8.220)	(-18.06)
Constant	0.345***	0.282***	0.210***	0.229***	0.253***
	(25.80)	(28.42)	(23.36)	(23.92)	(42.03)
Observations	16,417	18,638	16,738	13,804	65,597
R-squared	0.355	0.316	0.317	0.344	0.323
AIC	-9207.42	-8718.825	-7422.955	-7303.728	-31294.92
BIC	-9168.89	-8679.66	-7384.328	-7266.064	-31249.46

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Adaptive LASSO TDM

This table reports regression estimates using the variables selected by the adaptive LASSO, where the ratio of total debt to market value of assets (TDM) is used as the dependent variable. The period from 1980 to 2015 is used as the training sample for LASSO, where the variables that produce the lowest cv mean prediction error are selected. Further, the "one standard error rule" is applied to get a more parsimonious model. All the control variables used in the linear regression are lagged by one year, the variables are defined in appendix Q. The table includes the regression coefficients with significant levels, clustered standard errors in parenthesis and T-values. Column 1-4 displays regressions results within each decade, and column 5 results for the whole sample. At the bottom rows, the number of observations, R-squared, AIC and BIC are listed.

VARIABLES	(1) 1980-1989	(2) 1990-1999	(3) 2000-2009	(4) 2010-2019	(5) All Years
TDM					
IndustLev	0.773***	0.655***	0.681***	0.621***	0.667***
	(29.69)	(25.84)	(26.60)	(23.70)	(42.29)
Cash	-0.309***	-0.239***	-0.191***	-0.184***	-0.222***
	(-14.92)	(-14.04)	(-12.89)	(-10.51)	(-21.12)
Mktbk	-0.0506***	-0.0426***	-0.0315***	-0.0410***	-0.0403***
	(-15.26)	(-18.48)	(-18.34)	(-14.59)	(-27.78)
Constant	0.212***	0.200***	0.172***	0.199***	0.199***
	(24.95)	(23.81)	(21.85)	(22.53)	(39.11)
Observations	17,117	19,914	17,653	14,734	69,418
R-squared	0.308	0.295	0.303	0.338	0.307
AIC	-7705.348	-7741.631	-6765.146	-7178.342	-28700.66
BIC	-7674.357	-7710.035	-6734.032	-7147.95	-28664.07

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

When using the market-based leverage, the normal LASSO selects the four variables, industry median leverage, cash, market to book and Z-score, while the adaptive LASSO excluded Z-score. Therefore, only industry median leverage and market to book were included from the six original core factors. The normal LASSO for market-based leverage has a R-squared of 0.323 for all the years, while the adaptive LASSO has a lower R-squared of 0.307. The adaptive LASSO includes one less variable than the normal LASSO, but the normal LASSO has a lower BIC of -31 249.46 compared to the adaptive LASSO's BIC of -28 664.07. Therefore, the normal LASSO seems slightly better than the adaptive LASSO according to the BIC approach. For both the normal LASSO model and adaptive LASSO model, we observe relatively stable measures of R-squared across the decades. From table 11**,** we observe that the model using the core factors performed slightly worse than the normal LASSO model and slightly better than the adaptive LASSO model, with a R-squared of 0.319 and a BIC of -29 902.42. The performance measures for the three models are relatively equal, but the normal LASSO and adaptive LASSO are more parsimonious models, and therefore arguably better. Table 13 and table 14 shows that industry median leverage is the most impactful variable for all the years, except for the two first decades for the normal LASSO. For both models, the impact of the variables remains relatively stable throughout the decades, except for Z-score for the normal LASSO model, which declines over the years.

To further examine the selected factor from normal and adaptive LASSO we have looked at the standardized beta coefficients for each firm specific subsample for the market-based leverage (see table 15). Industry median leverage remains the most impactful variable and is stable across the subsamples. The impact of cash holdings varies across the subsamples, where the importance of the variable sees a steep decline from small firms to large firms. This is consistent with Faulkender and Wang (2006), who report that the marginal value of cash decreases for large firms. The impact of cash holdings also declines for firm that are restructuring their debt/equity ratio. Market to book ratio´s impact on leverage increases with firm size and growth, as well as for firms who adjusts their capital structure. Z-score´s impact on leverage increases sharply from small to medium firms, while we observe a rather small increase from medium to large firms. When comparing growing firms, Z-score is most impactful on leverage for firms in medium growth. Z-score is less impactful for firms in high-tech industries, while it increases for firms that are going through a financial restructuring.

7.2.1.Variable discussion

The coefficient for industry median leverage is significant and positive throughout all the different models. MacKay and Phillips (2005) showed that there exists an industry interdependence, where decisions regarding capital structure are affected by the changes made by competing firms. M. Frank and V. Goyal (2009) made the argument that from a trade-off theory perspective, one can interpret industry median leverage as a benchmark for firms' target capital structure. This is supported by Hovakimian, Opler, and Titman (2001), where their results indicate that industry median leverage is actively used as a proxy for firms' targeted financial structure. Industry median leverage is our most robust factor with the largest impact on leverage. However, one should not assume that the median leverage alone affects the capital structure. M. Z. Frank and V. K. Goyal (2009) presents the interpretation that the variable may reflects a set of correlated factors that have not been included in the original variable list. Possible examples of these are the nature of the competition or product market interaction.

The variable cash holdings has a negative effect on leverage in all the models and is significant at the 1% level. An increase in cash holdings increases the firms’ financial flexibility, and should therefore reduce the cost of debt. According to the trade-off theory, the firms will increase their leverage to better utilize their tax shield. Another argument that supports the increase in leverage is the reduction of agency costs. By reducing the funds available to the firm, the manager has less leeway to engage in excessive spending that is not in the best interest of the firm. This is supported by Ivalina and Lins (2007), who found that cash holdings exacerbate the agency cost. However, our results indicate that cash holding has a negative effect on leverage. This is aligned with the pecking order theory, as cash holdings increases the funds available to the firms, thus borrowing less. This is supported by Öztekin and Flannery (2012), who claims that liquid assets can be used as an internal source of funds instead of debt. Additionally, Deesomsak, Paudyal, and Pescetto (2004) states that liquid assets can be manipulated in favor of the shareholders against the interest of the creditors, resulting in an increased agency cost of debt. Tsyplakov (2008) argue that when an increase in the productivity capacity takes time, firms will build up their cash holdings until the time to invest is right. Thus, a negative relation between cash holdings and leverage is consistent with a dynamic trade-off theory perspective, where firms will wait to make adjustment.

Z-score has a significant negative effect on leverage for all the periods. This indicates that the firms with a higher leverage ratio has an increased risk of bankruptcy. These firms usually have more volatile cash flows, and consequently face a higher expected cost of financial distress. From a trade-off perspective, they should therefore reduce their leverage to lower the cost of debt and better utilize their tax-shield, as they have less profit to protect from taxes. Kayo and Kimura (2011), who used Z-score to measure the distance from bankruptcy, hypothesized that firms that were further away from bankruptcy had lower leverage. However, they did not find significant results that were consistent with their prediction, as they observed a positive relation between long term book leverage and Z-score, indicating that firms that are more financial healthy has a greater capacity for using debt to finance their investments. Our results corroborates with Byoun (2008), who found that a negative relation between Z-score and leverage, indicating that financially healthy firms with high Z-score can more easily use retained earnings over debt to finance their future investments. This is consistent with the pecking order theory, as they will not increase their leverage.

Market to book has a negative effect on leverage, but the variable is not significant and positive for book-based leverage in the period 2010 to 2019. The latter part is consistent with M. Z. Frank and V. K. Goyal (2009), as the variable is more suited for the more forward looking market-based value of leverage. From a pecking order perspective there is an argument to be made that firms with high market-to-book ratio is subjected to fewer asymmetric information problems. They will therefore be more inclined to issue equity over debt, as issuing equity often lead to increased scrutiny by the public. This may be favorable for firms that are confident in their growth opportunities, as the equity issuance is a way of distributing this information to outside investors. Another argument for firms with high market-to-book ratios to issue equity over debt is that they wish to reserve their borrowing capacity for the future. Firms in high growth have a risk of becoming over-levered, as they generate less retained earnings. They will therefore issue equity to counteract this (Kayhan & Titman, 2007). According to the market timing theory, firms with high market-to-book ratio will reduce their leverage, as they look to take advantage of equity mispricing. However, we have, as previously mentioned, observed a positive coefficient for the market-to-book variable in the period 2010-2019 when using book-based leverage as the dependent variable. This is consistent with the trade-off theory as firms with higher market-to-book ratios can borrow to a lower cost and will therefore use more debt, as supported by the findings to L. Chen and Zhao (2006). However, our findings mainly indicate that the issuance of equity when the market-to-book ratio is high outweighs the issuance of debt.

7.3.Out-of-sample analysis

In this section we evaluate the results of our models out-of-sample. The period 1980-2015 is used as training data to estimate the coefficients. The predicted values are then applied to the period 2016-2019 and each individual year to estimate mean absolute error and root mean squared error. We use the unpenalized OLS coefficients for forecasting, as they produce marginally better predictions for linear models (A. Belloni, Chen, Chernozhukov, & Hansen, 2012; Alexandre Belloni & Chernozhukov, 2013).

Table 7. MAE and RMSE

This table reports the prediction errors measured by mean absolute error (MAE) and root mean squared error (RMSE). The period 1980-2015 is used as training data to estimate the OLS coefficients for each model. The estimates are then applied to the period 2016-2019 and each individual year within this period to calculate the prediction errors.

	MAE				
	Normal TDM	**Adaptive TDM**	**Core TDM**	**Normal TDA**	**Core TDA**
2016-2019	0.131	0.143	0.142	0.112	0.126
2019	0.122	0.136	0.132	0.103	0.115
2018	0.138	0.150	0.148	0.114	0.126
2017	0.126	0.135	0.138	0.113	0.127
2016	0.131	0.145	0.144	0.113	0.129
	Normal TDM	**Adaptive TDM**	**Core TDM**	**Normal TDA**	**Core TDA**
2016-2019	0.177	0.185	0.185	0.162	0.172
2019	0.162	0.172	0.169	0.149	0.156
2018	0.187	0.196	0.193	0.164	0.171
2017	0.170	0.175	0.179	0.163	0.173
2016	0.179	0.188	0.189	0.164	0.177

7.3.1.TDA

Looking at all the individual years and the whole testing period for book-based leverage, we observe that the normal LASSO model consistently produces lower MAE and RMSE estimates than the core model. This indicates that the normal LASSO model gives more precise predictions than the core model. However, the differences here are rather miniscule, so we cannot decisively declare one model better than the other. One argument that speaks in support of the normal LASSO model, is that this model only consists of three variables compared to the core model's six. This suggests that cash holdings and Z-score can replace market-to-book, tangibility, profitability, assets, and inflation as important factors, while marginally improving the model's predictive performance.

When testing the predictive power of the LASSO model and core model for book-based leverage across the firm-specific subsamples, we see from table 16 that the normal LASSO model consistently produce marginally more accurate predictions compared to the core model. Some exceptions are observed for firms in medium growth, where the core model had the lowest MAE and RMSE, while for firms in high growth it had a lower RMSE. However, the differences are still minuscule, where we rarely observe improvements between the models over one percentage point. When comparing the prediction errors from the firm-specific subsamples to the whole sample, we generally observe that the normal LASSO model performs worse when it is applied to firms divided by specific characteristics. Some exceptions are for large firms and firms that are restructuring their capital structure, where the model had better MAE and RMSE. Additionally, the RMSE was lower for firms with low growth.

7.3.2.TDM

When comparing the models out-of-sample using the whole testing period for market-based leverage, the models performed relatively similar (see table 7). The adaptive LASSO model and the core model had an approximately equal prediction error regarding MAE and RMSE. The normal LASSO produced the lowest MAE and RMSE, but the improvements were only marginal. Looking at the individual testing years, the adaptive LASSO model and the core model produced relatively equal prediction errors, while the normal LASSO consistently produces the lowest MAE and RMSE. Thus, our results indicate that cash holdings can replace profits, tangibility, assets and inflation for predicting capital structure, while maintaining the performance of the model. The inclusion of Z-score improves the prediction accuracy, but not by large margins.

The normal LASSO model for TDM produced most consistently predictions with the lowest MAE and RMSE (see table 7) across the different subsamples, however, the results were often only marginally better than the other models. The lowest MAE and RMSE we observe in the subsample of firms with high growth, indicating that all the models for TDM can more accurately predict leverage for firms' market-to-book ratio. The largest difference differences between the models we observe in the subsample for firm going through refinancing, where the normal LASSO model has the lowest MAE and RMSE. This indicates that Z-score is an important factor for predicting leverage for firms that are restructuring their capital structure.

8.Summary and conclusion

In this section we will sum up our findings and answer the research question. The purpose of this research has been to determine which variables explain and predict capital structure for US firms, by using an alternative approach compared to conventional methods.

Our analysis resulted in three different models: one for book-based leverage and two for market-based leverage. The normal LASSO model for book-based leverage consist of the variables industry leverage, cash holdings and Z-score. The normal LASSO model for market-based leverage has the same selection of variables, while adding market-to-book. The adaptive LASSO model also adds market-to-book, but excludes Z-score. When comparing the normal LASSO model to the core factor model for book-based leverage, we observe a better model fit and a lower BIC. The adaptive model for market-based leverage performed relatively equal to core model, while the normal LASSO model produced slightly better regarding the performance measures.

From our list of variables, industry median leverage is the most impactful variable, where it has a significant positive effect on leverage. The variable is consistent with the trade-off theory, were firms often use the leverage median of the industry they are competing in as a benchmark for their target debt/equity ratio. We find that cash holdings has a significant negative effect on leverage. Our results are supported by the pecking order theory, which states that firms prefer to use retained earnings over debt and new equity. The variable is also consistent with the dynamic trade-off theory, as firms will not make adjustments until they move too far away from their target leverage. We find that Z-score has a negative relation with leverage. From perspective off the trade-off theory we see that firms with low Z-score should reduce their leverage to better utilize their tax shield. Firms with higher Z-score are more financially healthy, thus retained earnings are more available. Market-to-book has a significant negative effect on leverage, as firms try to take advantage of equity mispricing.

When testing the LASSO models out-of-sample compared to the benchmark we observe small differences regarding MAE and RMSE. The normal LASSO model for TDA consistently produced slightly more accurate prediction compared to the core model. However, some exceptions were observed when tested on the firm-specific subsamples. The adaptive LASSO model for market-based leverage performed about equal to the core model, while the normal

LASSO model had slightly lower prediction errors. In general, the normal LASSO models performed slightly better than the benchmark model, but the differences were rather small.

Our models perform relatively similar to the core model, with slightly better goodness of fit and prediction errors, while being more parsimonious. Thus, our results indicate that the normal LASSO models are better at explaining and predicting capital structure in our data, while the adaptive LASSO model performed relatively equal to the core model. This suggest that the variables cash holdings and Z-score can replace the core factors replace profits, tangibility, assets and inflation, while slightly improving the model's goodness of fit and prediction accuracy.

Although, our results include different variables than our benchmark, we can´t with certainty concluded that our models are better than M. Z. Frank and V. K. Goyal (2009) core factor model for explaining and predicting leverage. Thus, our models should not replace the core factors, but can provide and interesting alternative approach when researching capital structure.

9. Further research

We have used LASSO to determine which variables that explain and predict capital structure. However, our focus has mainly been on the whole data, and not certain industries or other firm-specific characteristics. Thus, LASSO may be applied to specific subsamples to examine how the variables varies across cross-sections, which may result in a better understanding of how our selected factors affect capital structure. Firm fixed effects is not included in this analysis, as M. Z. Frank and V. K. Goyal (2009) point out that the economic interpretation may be unclear. Z-score is one of the most important variables in our research, however Z-score is a product of multiple factors. Thus, Z-score warrants further examination as the variable may include certain interaction effects. For further research, one should also consider expanding the variable list, as the true model may consist of variables that are not included. Cash holdings and Z-score is relatively unexplored variable regarding capital structure. Thus, the variables may warrant further examination.

J. R. Graham and Leary (2011) found that the predictors in capital structure appear to have nonlinear relations with the leverage measures. Therefore, possibility of nonlinear modeling in capital structure can lead to more significant results and other important variables than previous literature.

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Appendix 1. Variable specification

Table 8. Variable list, abbreviation, definition, and sources

Variable	Abbreviation	Definition	Source
Market Value of Equity	MVE	The stock's fiscal year close price (PRCC_F) multiplied by common shares outstanding (CSHPRI). Data source: Compustat.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Market Value of Assets	MVA	Debt in current liabilities (DLC) plus long-term debt (DLTT) plus preferred stock liquidating value (PSTKL) minus differed taxes and investment tax credit (TXDITC) plus the market value of equity (MVE). Data source: Compustat.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Leverage Measures:			
Market Leverage	TDM	Debt in current liabilities (DLC) plus long-term debt (DLTT) divided by the market value of assets (MVA). Data source: Compustat.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Book Leverage	TDA	Debt in current liabilities (DLC) plus long-term debt (DLTT) divided by total assets (AT). Data source: Compustat.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Profitability:			
Profitability	Profit	Operating income before depreciation (OIBDP) divided by total assets (AT). Data source: Compustat.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Firm size:			
Total Assets	Assets	The logarithm of total assets (AT). Data source: Compustat.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Mature Firm	Mature	A dummy which equals 1 if the firm has been listed on the Compustat database for more than 5 years, 0 otherwise.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Growth:			
Market to Book	Mktbk	Market value of assets (MVA) divided by total assets (TA). Data source: Compustat.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Assets growth	ChgAssets	Change in the logarithm of total assets (AT). Data source: Compustat.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Physical investment	Capex	Capital expenditures (CAPX) divided by total assets (AT). Data source: Compustat.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Nature of Assets:			
Assets tangibility	Tang	Net property, plant, and equipment (PPENT) divided by total assets (AT). Data source: Compustat	(Amini et al., 2019; M. Frank & V. Goyal, 2009)

Innovation investment	RnD	Research and development expenses (XRD) divided by total sales (SALE). Following the standard practice in the literature, we set the R&D expenses to zero whenever it is missing in the Compustat database. Data source: Compustat.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Uniqueness	Unique	dummy variable that is equal to one if the SIC code of the firm is between 3400 and 4000 (firms producing computers, semiconductors, chemicals and allied, aircraft, guided missiles, and space vehicles and other sensitive industries), and zero otherwise. Data source: Compustat	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Non-production cost	SGA	Selling, general, and administrative expenses (XSGA) divided by total sales (SALE). Data source: Compustat.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Cash holdings	Cash	Cash and short-term investments (CHE) divided by total assets (AT). Data source: Compustat.	(Amini et al., 2019)
Taxes:			
Top tax rate	TaxRate	The top statutory tax rate in the U.S. The rates are 1980 to 1986, 40% in 1987, 34% from 1988 to 1992, 35% from 1993 to 2017, and 21% in 2018 and 2019. Data source: Internal Revenue Service Data Book.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Depreciation	Depr	Depreciation and amortization (DPC) divided by total assets (AT). Data source: Compustat.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Investment tax credit	InvTaxCr	Investment tax credit (ITCB) divided by total assets (AT). Data source: Compustat.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Risk:			
Stock variance	StockVar	The annual variance of daily stock returns. Data source: CRSP	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Bankruptcy probability	Z-score	Altman (1968) unlevered Z-score defined as 3.3 times the difference in operating income before depreciation (OIBDP) and depreciation & amortization (DP) plus sales (SALE) plus 1.4 times retained earnings (RE) plus 1.2 times the difference in total current assets (ACT) and total current liabilities (LCT) divided by	(Amini et al., 2019)

		total assets (TA). Data source: Compustat.	
Stock beta	Beta	Annual stock volatility in relation to the market index obtained from daily stock returns and index returns. Data source: CRSP	
Supply-Side Factors:			
Debt rating	Rating	A dummy variable which equals 1 if a firm's long-term credit rating (SPLTICRM) is BB or better. The variable equals 0 if the firm's rating is lower than BB or if the rating is missing. Data source: Compustat.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Stock Market Conditions:			
Stock returns	StockRet	Cumulative annual stock returns using monthly raw returns. Data source: CRSP.	(Amini et al., 2019)
Market returns	CrspRet	Cumulative annual market returns using monthly valueweighted CRSP returns. Data source: CRSP.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Industry:			
Industry leverage	IndustLev	The median of corporate leverage (TDM) by 4-digit SIC code and by year. Data source: Compustat.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Industry growth	IndustGr	The median of assets growth (ChgAsset) by SIC code and by year. Data source: Compustat.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Debt market conditions:			
Term spread	TermSprd	The difference between the 10-year bond returns and the 1-year bond returns. Data source: Federal Reserve files at	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Macroeconomic Conditions:			
Expected inflation	Inflation	The expected change in the consumer price index over the coming year. Data source: Livingston Survey conducted and maintained by Federal Reserve Bank of Philadelphia.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Macro profit growth	MacroProf	Change in logarithm of annual corporate profits with inventory valuation and capital consumption adjustments for nonfinancial firms. Data source: Federal Reserve Bank of St. Louis Economic Data.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)

Growth in GDP	MacroGr	Change in logarithm of real gross domestic product. Data source: Federal Reserve Bank of St. Louis Economic Data.	(Amini et al., 2019; M. Frank & V. Goyal, 2009)
Dividend:			
Dividend		A dummy variable which equals 1 if the firm has paid dividends (DVPD), and 0 otherwise.	

Table 9. Firm-specific subsamples

Variables	Descriptions	Source
Size dummies	A firm is classified as small, medium, or large in a given year if the size of the firm (Assets) lies in the bottom, middle, or top tercile of its empirical distribution in that year, respectively.	(Amini et al.,2019)
Growth dummies	A firm is classified as low-growth, medium-growth, or high-growth in a given year if the market-to-book ratio of the firm (Mktbk) lies in the bottom, middle, or top tercile of its empirical distribution in that year, respectively.	(Amini et al.,2019)
High tech dummy	A dummy variable which is 1 if a firm offers technology products and services, and equals 0 otherwise. More specifically, a firm is defined as a high-tech firm if its corresponding 4-digit SIC code equals one of the 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3671, 3672, 3674, 3675, 3677, 3678, 3679, 3812, 3823, 3825, 3826, 3827, 3829, 3841, 3845, 4812, 4813, 4899, 7371, 7372, 7373, 7374, 7375, 7378, or 7379 values	(Amini et al.,2019)
Refinancing dummy	A dummy variable which equals 1 if both the firm’s net long-term debt issuance (NetDebt) and net payout (NetPay) relative to total assets exceed the 3% threshold, and equals 0 otherwise.	(Amini et al.,2019)
Refinancing Proxies:		
Net debt issuance	Long-term debt issuance (DLTIS) minus long-term debt reduction (DLTR) scaled by total assets (AT). Data source: Compustat.	(Amini et al., 2019)
Net payout	Cash dividends (DV) plus purchase of common and preferred stock (PRSTKC) minus sale of common and preferred stock (SSTK) scaled by total assets (TA). Data source: Compustat.	(Amini et al., 2019)

Appendix 2. Empirical results

2.1.Regressions

Table 10. Core factors TDA

This table reports regression estimates using the core factors selected by M. Z. Frank and V. K. Goyal (2009), where the ratio of total debt to book value of assets (TDA) is used as the dependent variable. All the control variables used in the linear regression are lagged by one year, the variables are defined in appendix Q. The table includes the regression coefficients with significant levels, clustered standard errors in parenthesis and T-values. Column 1-4 displays regressions results within each decade, and column 5 results for the whole sample. At the bottom rows, the number of observations, R-squared, AIC and BIC are listed.

VARIABLES	(1) 1980-1989	(2) 1990-1999	(3) 2000-2009	(4) 2010-2019	(5) All Years
TDA					
IndustLev	0.677***	0.646***	0.660***	0.678***	0.682***
	(29.10)	(28.12)	(28.67)	(27.52)	(48.35)
Mktbk	-0.0137***	-0.0156***	-0.00862***	0.000674	-0.00933***
	(-7.114)	(-10.32)	(-5.853)	(0.320)	(-9.613)
Tang	0.103***	0.0807***	0.0569***	0.0425***	0.0611***
	(7.075)	(6.297)	(4.644)	(3.329)	(7.438)
Profit	-0.217***	-0.127***	-0.0842***	-0.0393**	-0.0929***
	(-10.72)	(-7.972)	(-6.039)	(-2.213)	(-10.02)
Assets	-0.00168	0.00456***	0.0113***	0.0177***	0.00789***
	(-1.220)	(3.505)	(8.492)	(10.68)	(8.885)
Inflation	-0.201***	-1.193***	2.181***	-0.270	0.168***
	(-3.644)	(-4.743)	(12.89)	(-0.497)	(2.710)
Constant	0.126***	0.130***	-0.0343***	-0.0359**	0.0413***
	(10.84)	(9.209)	(-3.280)	(-2.164)	(5.503)
Observations	16,688	19,776	17,588	14,716	68,768
R-squared	0.245	0.233	0.274	0.328	0.257
AIC	-13989.63	-13441.43	-13451.62	-10734.37	-50397.53
BIC	-13935.58	-13386.18	-13397.2	-10681.2	-50333.56

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11. Core factors TDM

This table reports the regression estimates using the core factors selected by M. Z. Frank and V. K. Goyal (2009), where the ratio of total debt to market value of assets (TDM) is used as the dependent variable. All the control variables used in the linear regression are lagged by one year, the variables are defined in appendix Q. The table includes the regression coefficients with significant levels, clustered standard errors in parenthesis and T-values. Column 1-4 displays regressions results within each decade, and column 5 results for the whole sample. At the bottom rows, the number of observations, R-squared, AIC and BIC are listed.

VARIABLES	(1) 1980-1989	(2) 1990-1999	(3) 2000-2009	(4) 2010-2019	(5) All Years
TDM					
IndustLev	0.741***	0.670***	0.710***	0.597***	0.685***
	(27.97)	(26.13)	(28.45)	(23.45)	(44.54)
Mktbk	-0.0598***	-0.0525***	-0.0424***	-0.0452***	-0.0488***
	(-20.51)	(-26.26)	(-23.19)	(-18.36)	(-37.72)
Tang	0.107***	0.0477***	0.0551***	0.112***	0.0743***
	(6.371)	(3.355)	(3.989)	(7.787)	(8.030)
Profit	-0.401***	-0.240***	-0.196***	-0.164***	-0.228***
	(-15.74)	(-13.97)	(-13.91)	(-9.470)	(-22.23)
Assets	0.00691***	0.00581***	0.0111***	0.0156***	0.00911***
	(4.148)	(3.790)	(7.016)	(8.777)	(8.797)
Inflation	0.751***	0.463	4.743***	-3.023***	1.063***
	(10.89)	(1.558)	(22.26)	(-5.160)	(14.57)
Constant	0.127***	0.146***	-0.0312**	0.116***	0.0827***
	(9.116)	(8.765)	(-2.511)	(6.150)	(9.156)
Observations	16,688	19,776	17,588	14,716	68,768
R-squared	0.332	0.298	0.321	0.361	0.319
AIC	-8204.18	-7876.78	-7243.088	-7686.913	-29966.38
BIC	-8150.123	-7821.534	-7188.663	-7633.737	-29902.41

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

2.2.Standardized beta coefficients

Table 12. Standardized beta coefficients normal LASSO TDA

This table reports the standardized beta coefficients using the variables selected by the normal LASSO for the dependent variable TDA.

VARIABLES	(1) 1980-1989	(2) 1990-1999	(3) 2000-2009	(4) 2010-2019	(5) All Years
TDA					
IndustLev	0.341	0.333	0.402	0.439	0.386
Cash	-0.239	-0.300	-0.268	-0.260	-0.275
Z-score	-0.273	-0.218	-0.164	-0.117	-0.179
Observations	16,417	18,638	16,738	13,804	65,597
R-squared	0.305	0.278	0.292	0.329	0.291

Table 13. Standardized beta coefficients normal LASSO TDM

This table reports the standardized beta coefficients using the variables selected by the normal LASSO for the dependent variable TDM.

VARIABLES	(1) 1980-1989	(2) 1990-1999	(3) 2000-2009	(4) 2010-2019	(5) All Years
TDM					
IndustLev	0.297	0.276	0.348	0.358	0.321
Cash	-0.197	-0.196	-0.188	-0.197	-0.200
Mktbk	-0.299	-0.318	-0.263	-0.256	-0.285
Z-score	-0.240	-0.199	-0.159	-0.145	-0.172
Observations	16,417	18,638	16,738	13,804	65,597
R-squared	0.355	0.316	0.317	0.344	0.323

Table 14. Standardized beta coefficients adaptive LASSO TDM

This table reports the standardized beta coefficients using the variables selected by the adaptive LASSO for the dependent variable TDM.

VARIABLES	(1) 1980-1989	(2) 1990-1999	(3) 2000-2009	(4) 2010-2019	(5) All Years
TDM					
IndustLev	0.365	0.335	0.368	0.386	0.357
Cash	-0.178	-0.151	-0.140	-0.139	-0.150
Mktbk	-0.246	-0.268	-0.222	-0.251	-0.249
Observations	17,117	19,914	17,653	14,734	69,418
R-squared	0.308	0.295	0.303	0.338	0.307

Table 15. Standardized beta coefficient normal LASSO TDM for firm specific subsamples

The table shows the standardized beta coefficients for the TDM normal LASSO model across the firm-specific subsamples for all years. Clustered T-statistic in parenthesis.

VARIABLES	(1) Small Firms	(2) Medium Firms	(3) Large Firms	(4) Low Growth	(5) Medium Growth	(6) High Growth	(7) No Tech	(8) High Tech	(9) No Refin	(10) Refin
TDM										
IndustLev	0.298	0.304	0.304	0.364	0.392	0.316	0.313	0.300	0.323	0.302
	(22.63)	(24.28)	(20.40)	(30.68)	(32.60)	(23.93)	(35.24)	(13.30)	(38.14)	(18.08)
Cash	-0.264	-0.145	-0.0705	-0.269	-0.215	-0.234	-0.193	-0.235	-0.209	-0.0556
	(-24.46)	(-13.29)	(-5.275)	(-22.83)	(-20.38)	(-20.94)	(-24.78)	(-11.84)	(-28.06)	(-3.291)
Mktbk	-0.225	-0.270	-0.328	-0.0373	-0.0472	-0.215	-0.298	-0.244	-0.276	-0.382
	(-21.00)	(-18.38)	(-17.83)	(-4.113)	(-5.947)	(-23.46)	(-29.68)	(-12.46)	(-30.34)	(-17.28)
Z-score	-0.113	-0.227	-0.245	-0.139	-0.214	-0.180	-0.186	-0.124	-0.169	-0.200
	(-9.422)	(-17.00)	(-15.28)	(-9.257)	(-14.68)	(-13.63)	(-17.70)	(-5.592)	(-17.29)	(-10.44)
Observations	25,333	22,028	18,236	19,868	21,687	24,042	56,315	9,282	59,603	5,994
R-squared	0.297	0.356	0.398	0.269	0.308	0.281	0.320	0.298	0.326	0.312

2.4.MAE and RMSE

Table 16. MAE and RMSE firm-specific subsamples

This table reports the prediction errors measured by mean absolute error (MAE) and root mean squared error (RMSE) within each firm-specific subsample. The period 1980-2015 is used as training data for each subsample to estimate the OLS coefficients for each model. The estimates are then applied to the period 2016-2019 to calculate the prediction errors.

	MAE				
	Normal TDM	**Adaptive TDM**	**Core TDM**	**Normal TDA**	**Core TDA**
Small Firms	0.162	0.157	0.166	0.156	0.162
Medium Firms	0.159	0.159	0.162	0.141	0.16
Large Firms	0.131	0.137	0.138	0.11	0.114
Low Growth	0.174	0.174	0.179	0.111	0.114
Medium Growth	0.157	0.166	0.141	0.143	0.134
High Growth	0.073	0.075	0.076	0.138	0.142
No Tech	0.152	0.153	0.153	0.129	0.133
High Tech	0.134	0.135	0.135	0.125	0.137
Not Refinancing	0.153	0.154	0.155	0.126	0.132
Refinancing	0.085	0.117	0.113	0.093	0.124

	RMSE				
	Normal TDM	**Adaptive TDM**	**Core TDM**	**Normal TDA**	**Core TDA**
Small Firms	0.2	0.195	0.202	0.203	0.204
Medium Firms	0.2	0.202	0.208	0.184	0.196
Large Firms	0.145	0.147	0.151	0.133	0.143
Low Growth	0.218	0.217	0.224	0.142	0.145
Medium Growth	0.198	0.207	0.186	0.185	0.179
High Growth	0.102	0.104	0.103	0.189	0.188
No Tech	0.193	0.192	0.192	0.175	0.177
High Tech	0.175	0.177	0.179	0.166	0.178
Not Refinancing	0.194	0.194	0.195	0.171	0.175
Refinancing	0.122	0.152	0.146	0.148	0.17

Appendix 3. Methodology

3.1.OLS assumptions

Ordinary least squares (OLS) is a method for estimating parameters in a linear regression. The coefficients estimated by OLS minimize the sum of the squared residuals.

$$OLS\ minimizes \sum_{i=1}^{N} e_i^2 \ ,(i = 1, 2 \ \ldots, N)$$

The model can be expressed as:

$$Y_i = \beta_0 + \beta_1 X_i + \varepsilon_i$$

Where B_0 and B_1 gets assigned the values that minimizes the squared residuals in the dataset.

For OLS to produce the best estimates, seven assumptions need to be fulfilled:

1. The regression model is linear in the coefficients and the error term.
2. The mean of the error term is zero.
3. All independent variables are uncorrelated with the error term.
4. Observations of the error term are uncorrelated with each other.
5. The error term has a constant variance, meaning no heteroscedasticity.
6. No independent variable is a perfect linear function of other explanatory variables.
7. The error term is normally distributed.

Table 17. OLS assumptions

	Multicollinearity	**Autocorrelation**	**Heteroskedasticity**
What is wrong?	Independent variables are correlated	Correlated error terms	Not consistent variance for the error term throughout the period.
How to detect it?	VIF-index or correlation matrix	Durbin-Watson test, Residual plot, Correlogram, Lagrange multiplier test, or Wooldridge test.	Park test, White test, or Breush-Pagan test
Consequences with OLS?	Biased estimates, standard deviation high and consequently T-values too small, unstable estimations, non or few significant variables but high R-squared.	Biased estimates, standard deviation too small and consequently T-values to high and variables will too often be significant, therefore T-test, F-test and confidence intervals are not valid.	Same as for serial correlation.
How to handle?	Excluded redundant independent variable, increase sample size, combine independent variables, or do nothing,	Generalized Least Squares or Newey-West standard errors.	Heteroskedasticity-consistent standard errors, clustered standard errors or reformulate the variables.

(For further descriptions see Studenmund (2016).)

3.2.Stastistical tests

Table 18. VIF-index

Variable	**VIF**	**1/VIF**
SGA	2,72	0.367032
Z-score	2,71	0.369171
Profit	2,70	0.371048
Inflation	2,66	0.376518
Tang	2,09	0.477938
RnD	2,09	0.479432
TopTaxRate	2,04	0.489332
Capex	1,82	0.549028
MacroProf	1,73	0.578563
TermSprd	1,72	0.579726
MacroGr	1,53	0.651603
Depr	1,50	0.665203
Mktbk	1,40	0.711963
ChgAsset	1,40	0.715144
Cash	1,36	0.736631
IndustGr	1,29	0.775552
StockRet	1,25	0.799235
IndustLev	1,22	0.817689
Dividend	1,16	0.860814
Unique	1,11	0.900135
Beta	1,11	0.904234
StockVar	1,10	0.905457
CrspRet	1,10	0.906809
Mature	1,09	0.915348
InvTaxCr	1,02	0.979382
Mean VIF	**1,64**	

➔ A rule of thumb, VIF over 5 indicate possible issues relative to multicollinearity. This indicates no issues relative to multicollinearity.

Table 19. White test

TDA		TDM	
White test for heteroskedasticity *H_0: Homoskedasticity* *H_1: Heteroskedasticity*		White test for heteroskedasticity *H_0: Homoskedasticity* *H_1: Heteroskedasticity*	
chi2(347) =	8922.27	chi2(347) =	8922.27
Prob>chi2 =	0.0000	Prob>chi2 =	0.0000

➔ The White test indicates significant heteroskedasticity in the data.

Table 20. Wooldridge test

TDA		TDM	
Wooldridge test for autocorrelation in panel data *H_0: No first-order autocorrelation* *H_1: First-order autocorrelation*		Wooldridge test for autocorrelation in panel data *H_0: No first-order autocorrelation* *H_1: First-order autocorrelation*	
F(1,4370) =	2636.522	F(1,4370) =	4491.812
Prob > F(1,4370) =	0.0000	Prob > F(1,4370) =	0.0000

➔ The Wooldridge test indicates significant first-order autocorrelation in the data.

Table 21. Normality

	Skewness	Kurtosis	Joint

Variable	Obs	P-value	P-value	Chi-squared	P-value
TDA	76 341	0.0000	0.0000	5203.43	0.0000
TDM	76 341	0.0000	0.0000	6393.33	0.0000
Profit	76 072	0.0000	0.0000	56056.51	0.0000
Assets	76 341	0.0000	0.0000	980.80	0.0000
Mature	76 341	0.0000	0.0000	17117.88	0.0000
Mktbk	76 341	0.0000	0.0000	66496.56	0.0000
ChgAsset	70 442	0.0000	0.0000	25115.46	0.0000
Capex	75 413	0.0000	0.0000	53009.40	0.0000
Tang	76 178	0.0000	0.0000	6246.54	0.0000
RnD	76 341	0.0000	0.0000	116500.53	0.0000
Unique	76 341	0.0000	0.0000	14450.89	0.0000
SGA	69 516	0.0000	0.0000	95905.32	0.0000
Cash	76 333	0.0000	0.0000	39886.37	0.0000
TopTaxRate	76 341	0.0000	0.0000	3877.43	0.0000
Depr	74 854	0.0000	0.0000	41029.76	0.0000
InvTaxCr	75 555	0.0000	0.0000	141534.75	0.0000
StockVar	74 351	0.0000	0.0000	164814.98	0.0000
Z-score	72 066	0.0000	0.0000	59699.29	0.0000
Beta	69 864	0.0000	0.0000	2322.51	0.0000
Rating	76 341	0.0000	0.0000	16050.10	0.0000
StockRet	74 915	0.0000	0.0000	39947.63	0.0000
CrspRet	76 341	0.0000	0.0000	5248.75	0.0000
Dividend	76 341	0.0000	.	.	.
IndustLev	76 341	0.0000	0.0000	4617.77	0.0000
IndustGr	75 593	0.0000	0.0000	12371.93	0.0000
TermSprd	76 341	0.0000	0.0000	8340.01	0.0000
Inflation	76 341	0.0000	0.0000	35369.28	0.0000
MacroGr	76 341	0.0000	0.0000	8055.06	0.0000
MacroProf	76 341	0.0000	0.0000	13877.98	0.0000

$H_0: Skewness = Kurtosis = 0\ (Normal\ distribution)$
$H_1: Skweness\ and/or\ Kurtosis \neq 0$

$\alpha = 0{,}05$
$Reject\ H_0\ if\ P - value < 0{,}05$

➔ The test for normality indicates significant skewness and kurtosis in the variables.