Credit and Capital Markets, 56 (2023) 3/4: 313–351
https://doi.org/10.3790/ccm.2023.1441801
Scientific Papers

Capital Structure Determinants in German SMEs: Panel Analysis and Policy Recommendations*

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Abstract

This study investigates the financing decisions within German SMEs, examining firm-specific, macroeconomic, and news-related determinants. Utilizing a 10-year dataset encompassing 13,051 SMEs, we employ a dynamic panel data model with an unbiased Dynamic Panel Fractional (DPF) estimator to identify the key variables influencing the debt-to-equity ratio. The findings underscore the importance of factors such as the non-debt tax shield, firm size, interest rate spread, and the economic policy uncertainty index.

The study's findings propose the following policy implications: 1) Policy initiatives targeting firm size and non-debt tax shields affect SME leverage; 2) Policies addressing the term spread and economic uncertainty influence debt levels across various German industries; 3) Industry-specific SME policies are advisable, due to the significant industry effects on German SME leverage; 4) SME policy incentives yield short-term effects on capital structures, as SMEs adjust leverage within 8 months.

Keywords: SME policy, capital structure, SMEs, financing decisions, leverage, panel data.

JEL Classification: G32, G38, L25, L26, M13, C23

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* The authors would like to express their sincere gratitude to the anonymous referee for their valuable feedback and insightful comments, which significantly contributed to the improvement of this paper.

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I. Introduction

Due to the key economic role of SMEs around the globe (Co-operation & Development 2017), the analysis of the capital structure of small- and medium-sized enterprises, has attained an increasing importance worldwide (*Kumar* et al. 2019). Also in Germany, SMEs are vital for the economy; they comprise 99.6 % of the country's businesses and made an impressive contribution of 54.4 % and 47.4 % to the country's GDP in 2019 and 2022, respectively. This underscores the importance of researching the capital structure of German SMEs. Furthermore, deriving policy implications from the leverage decisions of German SMEs is crucial, as it is debated that policy could be improved to support SMEs' capital investments, and SBA fact sheets document that state aid and access to finance for German SMEs are just at the EU average.[1]

The academic debate on capital structure has been ongoing since *Modigliani/Miller* (1958). The theories-trade-offs, pecking order, and agency costs theory-assist decision-makers. Despite this, authors such as *Brealey* et al. (2019) and *Yapa Abeywardhana* (2017) list capital structure issues as unanswered topics.

Empirical research on SMEs' capital structure often yields contradictory results, with studies examining various firm-specific variables as determinants. *Yapa Abeywardhana* (2017) and *Forte* et al. (2013) highlight this inconsistency. Omitted variable bias may contribute to this contradiction by distorting the coefficients of these variables. To address this issue, some studies have focused on macroeconomic determinants such as economic uncertainty (*Zhang* et al. 2015; *Graham* et al. 2015) or industry effects (*MacKay/Phillips* 2005; *Hatfield* et al. 1994). While these studies have identified significant effects of industry and macroeconomic uncertainty on the capital structure, they often overlook considering these factors together, potentially leading to contradictory findings. Although research has examined the capital structure of German SMEs (*Hall* et al. 2004; *Schäfer* et al. 2004; *Iqbal/Kume* 2014), there's a gap in simultaneously analyzing microeconomic, macroeconomic, and industry effects within German SME data, leaving room for the omitted variable problem. Biased estimates could also contribute to contradictory results in empirical research on leverage, and we do observe many biased estimates used in capital structure literature.

Clear policy recommendations on SMEs' leverage are essential to prevent financial crises (*Geanakoplos* 2010), maintain accounting standards (*Pirveli* 2015), and foster financial market development. However, stating clear implications of research findings is necessary for informing policymakers (*Antoniou* et al. 2008). While some scholars, like *Yu* (2000) propose policy implications, recommendations often lack specificity and context, particularly for German SMEs. Bridging

[1] Compare SME Performance Review 2021/2022 – Germany country sheet.

this gap is crucial for informed decision-making and tailored policy formulation.

As discussed above, the capital structure literature reveals several gaps, including inaccuracies in leverage models due to omitted macroeconomic variables and industry effects, biased estimates of SMEs' leverage, and a lack of practical implications for policymakers. Our study seeks to address these gaps.

Our paper relates to four interconnected strands of literature: the microeconomic modeling of SMEs' capital structure, the impact of macroeconomic and industry factors on leverage decisions, panel data estimation methodologies, and literature on leverage policy recommendations.

In this article, we propose a model to identify the debt-to-equity ratios in German SMEs, analyzing their response to firm-specific, macroeconomic, and industry shocks. We aim to provide policy recommendations relevant to the capital structure for German SMEs at both the business entity and industry levels. To derive policy insights, this paper unlike mainstream literature, and like *Reddy* (2022) simultaneously tests for macroeconomic impact and industry effects. We aggregate SMEs' data from the firm level to the industry level for comprehensive analysis.

Additionally, we assess the expected policy outcomes by examining the duration of SMEs' response to policy changes. This evaluation involves analyzing industry and firm-level adjustment speeds of the capital structure using the dynamic panel fractional estimator (DPF), known for its precision in assessing capital adjustment speed. (*Elsas/Florysiak* 2015).

The study reveals several key findings: 1) capital structure responds to a non-debt tax shield, suggesting it is reasonable in Germany to apply tax policy incentives related to the non-debt tax shield. 2) As company size is significant capital structure determinant, policymakers can target policy incentives towards smaller firms. 3) German SMEs leverage is subject to statistically significant industry effects, indicating that different industries make leverage decisions differently. 4) capital structure is sensitive to macro variables such as the term spread and uncertainty index, with SMEs in several industries tending to take on more debt during periods of economic uncertainty. 5) SMEs adjust their capital structures within 8 months, and one-time policy effects last for the same duration, suggesting that the policy incentives can be effective in times of short-term fluctuations.

The primary contribution of this paper lies in its provision of comprehensive evidence regarding German SMEs' capital structure decisions, offering valuable insights relevant for policymakers.

The rest of this paper is structured as follows: Section 2 reviews existing literature on microeconomic and macroeconomic factors influencing capital structure. Section 3 covers data sources, methodology, and estimation techniques. Section 4 presents empirical findings from our analysis of German SMEs and discusses implications. Finally, Section 5 concludes with policy recommendations.

II. Background Literature and Empirical Evidence

Since the seminal work of *Modigliani/Miller* (1958) in the capital structure literature, researchers have devoted significant effort to identifying factors that explain firms' borrowing behavior. A considerable branch of the literature researches capital structures of SMEs. *Reddy* (2022), and *Degryse* et al. (2012) explored industry effects on SMEs' capital structure, while *Daskalakis/Tsota* (2022) and *Pan* et al. (2019) explored macroeconomic effects on SMEs. Additionally, *Pham/Hrdý* (2023) and others (*Iqbal/Kume* 2014; *Proença* et al. 2014, *Balios* et al. 2016; *Daskalakis* et al. 2017; *Matias/Serrasqueiro* 2017; *Öhman/Yazdanfar* 2017; *Yazdanfar* et al. 2019) examined the impact of firm-specific variables on capital structure.

Studies document that leverage is strongly affected by the firm-specific characteristics and economic conditions. Firm-specific determinants suggested in the literature are size (*Hull* et al. 2014; *Balios* et al. 2016), Non-debt tax shield (*De Miguel/Pindado* 2001; *Ramlall* 2009), net trade credit *(Nilsen* 2002; *Seifert* et al. 2013), tangibility (*Antoniou* et al. 2008; *De Jong* et al. 2008), profitability (trade-off theory; *Camara* 2012), economic conditions suggested in the literature are term-spread (*Bauer/Mertens* 2018), inflation (*Wang/Xu* 2020; *Falato* et al. 2018) and economic policy uncertainty index (*Zhang* et al. 2015; *Lee* et al. 2017) generated from news.

To draw policy implications, we focus on specific factors: interest rate spread (influenced by monetary policy), NDS (influenced by fiscal policy), the Economic Policy Uncertainty Index (influenced by economic policy), and stable company-specific variables like size and last period's leverage. This targeted approach enhances our ability to draw policy implications from capital structure dynamics.

1. *Firm-specific Variables*

a) Non-debt Tax Shields

DeAngelo/Masulis (1980) were among the pioneering researchers who investigated the impact of corporate taxes, personal taxes, and non-debt tax shields on capital structure. Their seminal model proposed that tax deductions related to depreciation and investment tax credits serve as substitutes for the tax benefits associated with debt financing. Consequently, firms with substantial non-debt tax shields, particularly those benefiting from tax deductions for depreciation, tend to rely less on debt in their capital structures (*Titman/Wessels* 1988). This suggests that firms with significant non-debt tax shields may not feel as compelled to increase their debt levels to leverage the tax deductibility of interest payments (*Rubio/Sogorb* 2011).

Trade-off theory hypothesizes significant effects of taxes on capital structure as it considers tax savings to be benefits of leverage. Trade-off theory hypothesizes that there is a negative relationship between leverage and non-debt tax shield.[2]

In prior studies, an inverse relationship between debt levels and non-debt tax shields has been consistently observed. *Pham/Hrdý* (2023) found this relationship among the Visegrad group SMEs, *Antoniou* et al. (2008) in Germany, Japan, and the UK, *Czerwonka/Jaworski* (2021) in Central and Eastern Europe SMEs and *De Miguel/Pindado* (2001) in Spanish firms. *Fama/French* (2002) concluded that firms benefiting from greater non-debt tax shields tend to have lower leverage, a finding supported by Ozkan (2001) and *Korajczyk/Levy* (2003).

In contrast, certain studies in the literature have identified a positive relationship between non-debt tax shields and leverage. For example, *Ramlall* (2009) suggested such a relationship in cases involving both long and short-term loans and debt. However, their calculation of the non-debt tax shield as depreciation divided by earnings before interest and tax contributed to this finding.

Most recently, *Sheik* et al. (2022) state that for Indian non-bank financial companies, they do not find explanatory power of non-debt tax shield as a determinant of capital structure.

In our study, we include a non-debt tax shield (depreciation/total assets) as a proxy of the current tax deductions associated with capital equipment, following *DeAngelo/Masulis* (1980), who suggest that current tax deductions are partially captured by the non-debt tax shield.

b) Firm Size

Firm size is a key determinant of capital structure decisions, reflecting diversification and financial distress risk. According to the trade-off theory, larger firms tend to have lower financial distress costs and fewer information asymmetries (such as more stable collateral assets and better transparency), making them more inclined to use leverage. For larger firms, fixed direct bankruptcy costs constitute a smaller portion of the firm's value, leading to relatively lower

[2] Compare for example Salawu & Agboola (2008).

costs of leverage (*Titman/Wessels* 1988). Additionally, larger firms face a lower probability of bankruptcy, enabling them to accommodate higher debt capacity (*Rajan/Zingales* 1995), thus reinforcing their demand for debt.

Larger firms are more transparent to investors, so the problems of information asymmetry will be less severe. These firms will have a higher chance of receiving external financing, either through bank debt or by issuing bonds or equity. As positive accounting theory suggests, larger firms are likely to make less risky investments (*Pirveli* 2020). Correspondingly, larger firms can obtain more bank credit, whereas smaller firms are forced to rely on internal financing (*De Haas/Peeters* 2006). Thus, larger firms tend to operate with more leverage because they are more transparent, have lower asset volatility, or have better access to public debt markets (*Flannery/Rangan* 2006).

Large firms typically have higher leverage due to their better access to financial markets, more stable cash flows, and reduced financial distress (*Rubio/Sogorb* 2011). Additionally, *Chung* (1993) suggests that larger firms may face lower agency costs related to asset substitution and underinvestment, further supporting their higher leverage. Conversely, smaller firms often maintain lower leverage ratios, as they face heightened risks of liquidation during financial distress, illustrating a positive correlation between firm size and leverage (*Ozkan* 2001).

Empirical research frequently highlights disparities in capital structure decisions between SMEs and large firms. For example, *Jõeveer* (2013) finds that SMEs' decisions in Western Europe are not governed by the same variables influencing leverage decisions in large firms. Similarly, *Korajczyk/Levy* (2003) demonstrate that capital structure decisions differ between financially constrained and less financially constrained firms in the U.S.

According to the pecking order theory, the relationship between firm size and leverage is expected to be positive. *Proença* et al. (2014) found a positive link between size and leverage in Portuguese SMEs, a trend supported by *Artikis* et al. (2007), *Sheikh/Wang* (2011), *Hull* et al. (2014). *Balios* et al. (2016) investigated panel data of 8052 Greek SMEs, and *Daskalakis/Psillaki* (2008) analyzed 5-year panel data totaling 8266 French and Greek SMEs. Similarly, *Czerwonka/Jaworski* (2021) analyzed SME data from Central and Eastern Europe and also reported similar findings. In the same vein, *Yazdanfar* (2019) observed a positive correlation between size and short-term debt in Swedish SMEs, with a negative correlation for long-term debt.

In our study, we focus exclusively on SMEs and hypothesize that their capital structure decisions differ from those of larger firms. Specifically, we examine how differences in SMEs' sizes influence their capital structures by analyzing the impact of firm size on their debt-to-equity ratio.

2. *Macroeconomic Variables and Industry Effects*

Firms do not operate in a vacuum. Thus, when examining capital structure decisions, managers have to consider not only the state of the firm but also market conditions (as shown in *Antoniou* et al. (2008)). Many studies have provided empirical evidence that market conditions influence the capital structures of large, listed firms. SMEs also react to market and economic conditions (*Daskalakis/Tsota* 2022; *Rubio/Sogorb* 2011; *Daskalakis* et al. 2017). *Mokhova/Zinecker* (2014) analyzed panel data from 7 European countries and applied Pearson correlation analysis to show significant effects of economic conditions on corporate capital structure decisions in Europe. *Camara* (2012) studied a sample of U.S. local and international firms and argued that economic conditions influence capital structures. *Cook/Tang* (2010) also show that economic conditions influence the speed of capital structure adjustment.

Which economic conditions would influence a manager's decision to take on debt or issue obligations presently, or refrain from doing so? We can follow the trade-off theory and address the question as follows: Since managers are concerned about borrowing costs, it is essential that macroeconomic conditions influencing debt financing decisions capture: 1) the current comparative *cost of acquiring debt* or issuing obligations (relative to other periods), 2) *expectations regarding future borrowing expenses*, as well as uncertainties about the future. We incorporate solely macroeconomic variables into the model that meet these criteria.

The interest rate spread, which reflects the difference between short-term and long-term interest rates, is a key macroeconomic indicator influencing borrowing costs in the market. When the market is perceived as risky, investors demand higher interest rates for lending money, causing short-term rates to rise relative to the yields of long-term risk-free bonds such as 10-year government bonds. This results in a smaller term spread, indicating higher borrowing costs for firms. Consequently, financial managers may be less inclined to opt for debt financing due to the increased cost of short-term borrowing in a risky market environment.

Moreover, the interest rate spread is a macroeconomic financial indicator that implies expectations about future borrowing costs. The interest rate spread serves as a predictor of future interest rate changes or, in general, the course of the economy (*Bernanke* 1990). Thus, the interest rate is a macroeconomic variable that satisfies both criteria we have formulated above.

Economic policy uncertainty significantly influences financial managers' decisions regarding debt issuance by signaling unassessed risks. This uncertainty, which reflects expected risks at the country level, directly impacts the cost of debt financing. Given its substantial influence on borrowing costs and financial decision-making, economic policy uncertainty is a crucial macroeconomic variable to include in our model.

In this study, we concentrate on investigating the influence of economic policy uncertainty and term spread on the leverage of German SMEs. These factors are chosen based on meeting the specified criteria and are supported in the literature. By doing so, we aim to examine the effects of market conditions on the leverage ratios of German SMEs. We acknowledge that the macroeconomic effects may not be equally strong for every firm, as firms exhibit differences in various aspects (as confirmed by the Hausmann test for our data). Nonetheless, we anticipate that the macroeconomic effects will exert a significant influence at the industry level.

a) Interest Rate Spread

Decent literature highlights the significance of the interest rate spread (or term spread) as a crucial macroeconomic determinant of capital structure decisions. The influence of the interest rate spread on leverage is explained as follows: the interest rate spread reflects expectations about changes in capital costs and signals future economic performance (*Bauer/Mertens* 2018), and managers incorporate these expectations into capital structure decisions. *Korajczyk/Levy* (2003) argued that the term spread serves as a signal of economic performance and expected growth opportunities, thus influencing firm leverage.

Korajczyk/Levy (2003) observed firms that altered their capital structure and revealed that the term spread has a statistically significant negative relation with the debt-to-equity ratio as well as with the long-term debt-to-equity ratio in financially constrained firms.

We aim to assess whether a higher term spread correlates with lower leverage in German SMEs and whether this relationship is statistically significant. Our hypothesis posits that the interest rate spread is a crucial determinant of capital structure for German SMEs.

b) Economic policy uncertainty index

There are several theoretical channels through which economic policy uncertainty influences firms' capital structure decisions. *Zhang* et al. (2015) describes two channels through which economic uncertainty influence leverage by changing financing costs. These channels are: 1) economic uncertainty leads to deteriorated external financing environment, resulting in lower leverage; 2) Economic uncertainty leads to information asymmetry between borrowers and creditors, increasing default risk, and consequently lowering leverage.

Recent empirical research has argued that economic and policy uncertainty influence capital structure decisions. *Graham* et al. (2015) detected that changes in economic uncertainty have influenced capital structures in the U.S. *Zhang* et al. (2015) documented the importance of policy uncertainty as a capital structure determinant and provided empirical evidence that firms lower their leverage in China during times of higher economic uncertainty. *Athari/Bahreini* (2023) find that economic policy uncertainty (EPU) negatively impacts Western Union TL firms. *Lee* et al. (2017) reveal that in the U.S., economic uncertainty influences leverage decisions in the financial industry. *Graham* et al. (2015) confirm that in the U.S., economic uncertainty is negatively correlated with capital structures of all sizes of firms in unregulated industries. *Pan* et al. (2019) argue that political uncertainty has a significant negative impact on leverage. Tax changes are also incorporated into the political uncertainty index. *Heider/Ljungqvist* (2015) show that tax changes have a first-order effect on the capital structures of American companies. Motivated by this empirical evidence, we investigate the influence of the economic policy uncertainty index developed by *Baker* et al. (2016) on the overall leverages of German SMEs.

3. *Industry Effects*

Several empirical studies investigate the industry effects on the capital structure of SMEs and demonstrate a statistically significant relationship. *Degryse* et al. (2012), based on their empirical research of small Dutch firms, conclude that compared to the manufacturing industry, all industries sustain different capital structures. By applying a fixed-effects model, they detect significant intra- and inter-industry effects on the capital structures of small enterprises. *Serrasqueiro* et al. (2011) analyze Portuguese SMEs that have been in the market for 7 years, comparing the capital structures of SMEs from the service sector to those from other sectors, and find that capital structure decisions of service SMEs differ from those of other firms. *Michaelas* et al. (1999) empirically verify that small firms in the United Kingdom are subject to industry effects. *Hall* et al. (2000) study 3500 British unlisted SMEs and identify important industry effects on SMEs' leverage ratios.[3] We follow the suggestion in these studies and check for industry effects in German SMEs. However, we do not test industry effects in isolation from the macroeconomic effects. Instead, we incorporate industry and macroeconomic effects together in one model. Similar to *Reddy* (2022), who incorporate industry-specific and macroeconomic factors into a unified model. While *Reddy's* study covered 10 European countries and included SMEs

[3] By applying F test to the difference in the residual sum of square (RSS) of a restricted and unrestricted (fixed effects) model.

and listed companies, our focus is on German SMEs, exploring the interplay between industry and macroeconomic effects on leverage.

III. Data and Methods

1. *The Data and Description of Variables*

In our study, we utilize panel data from the Amadeus database, provided by Bureau van Dijk Electroniques (*Van Dijk* 2017). This balanced dataset spans a decade preceding the 2015 Investment Tax Act reform in Germany, covering the years from 2004 to 2014.

The 2015 Investment Tax Act reform is highly relevant for financing decisions. The reform introduced significant changes to the taxation of investment income. The reform aimed to stimulate investment by: 1) cutting the tax rate to a flat 25 % on dividends and capital gains, abandoning the collection of the solidarity surcharge; 2) exempting accumulation units of investment funds (which reinvest income rather than distributing it to investors) from taxation; and 3) simplifying reporting requirements for investors.

We specifically focus on the pre-reform period. Our decision to analyze only this period is strategic and methodologically sound. Economic agents may respond differently to pre-reform, reform, and crisis periods. Combining these periods in the analysis could mask or distort the heterogeneity of responses, leading to misleading conclusions and blurred results. By focusing solely on the pre-reform period, we aim to provide a clear understanding of pre-existing financing decision behaviors, unaffected by the reform. This approach allows us to explore the nuances of financing decisions leading up to the reform without the potential confounding effects of subsequent policy changes.

The dataset utilized in this research consists of financial data from small and medium-sized German firms. These firms, totaling 27,889, are classified as SMEs, with up to 250 employees and revenue of up to 50 million Euros.

In the original unbalanced raw data from the Amadeus database, 34 % of the data contains missing observations. To address this issue, we employ two approaches. First, we drop the year for the firm if any relevant variable observation is missing for that year-firm combination. This results in a cleaned, balanced database with 72,921 observations from 14,597 firms. Second, we use the trimming technique to remove anomalous observations that fall outside the theoretical ranges of the variables. For example, we remove observations where total fixed assets exceed total assets or where sales are negative. Additionally, we exclude the top 3 % of debt-to-equity ratios to eliminate outliers that may skew the analysis. This results in a maximum debt-to-equity ratio of 13.308. After trimming, we retain data for 13,051 SMEs and 70,734 observations, having removed 2,186 outliers from the original 72,921 observations.

Table 1 outlines the variables utilized in this study. The second column displays the abbreviations of the variables listed in the first column, while the third column presents the formulas used to calculate each variable.

The primary dependent variable, debt-to-equity ratio (DE), is computed as total debt divided by total equity. In various studies, proxies for capital structure, whether expressed in book or market values or a combination thereof, are used. Book leverage, representing the ratio of total book debt to total assets, is commonly employed as a measure of capital structure. For instance, *De Miguel/Pindado* (2001) and *Fama/French* (2002) both use the book value of the debt-to-equity ratio as a measure of leverage. In our study, we adopt the same approach, considering the debt-to-equity ratio as a measure for leverage. It's important to note that for the industry model, we calculate the time-series industry means of debt-to-equity ratios (Mean DE) for each industry, as we are interested in the overall effects on industry debt-to-equity ratio caused by the explanatory variables of the model.

Table 1

Definition of Variables[4]

Variable	*Abbreviation*	*Calculation*
Main Dependent Variable		
Debt-to-equity ratio	DE	Total debt/Total equity
Independent variables – Firm-specific Variables		
Non-debt tax shield	NDS	Depreciation and amortization/ Total assets
Size	S	Natural logarithm of sales
Independent Variables – Macroeconomic Variables		
Term spread	Term Spread	10-year long-term government bond yield – yearly short-term interest rate
Independent Variables – News Variables		
Uncertainty index	Uncertainty Index	Economic Policy Uncertainty index of Germany

[4] Source: Firm's characteristics are collected from the Bureau van Dijk database (Amadeus database) and calculations are done by the authors. The data for calculating term spread is taken from the OECD database (OECD, 2014). The Economic Policy Uncertainty index of Germany is calculated by *Baker* et al. (2016). The methodology and data are available online at http://www.policyuncertainty.com/methodology.html and http://www.policyuncertainty.com/europe_monthly.html.

The second part of Table 1 outlines the independent variables, comprising firm-specific and macroeconomic factors. Firm-specific factors incorporated in the model encompass size and non-debt tax shield, while the aggregated models feature macroeconomic variables like term spread and uncertainty index. Size is derived from the logarithm of sales, while the non-debt tax shield is calculated as depreciation and amortization divided by total assets.

The term spread is calculated as the annual 10-year government bond yield minus the annual short-term interest rate. The Economic Policy Uncertainty (EPU) index is a text-based variable derived from three components: (1) Quantified newspaper information about economic uncertainty; (2) Temporary tax code provision; and (3) Expectation fallacy of experts about economic variables, such as the consumer price index and government spending.

We conducted an in-depth analysis focusing on the long-term debt-to-equity ratio (LTDE) to derive clearer policy recommendations. LTDE is calculated by dividing long-term debt by total equity.

Table 2 displays descriptive statistics of the model variables before removing outliers identified by Cook's distance, including mean, standard deviation, minimum, maximum, and the number of observations.

Table 2

Descriptive Statistics[5]

Variable	*Mean*	*Std. Dev.*	*Minimum*	*Maximum*
Dependent Variable				
Debt-to-equity ratio (DE)	1.087	1.924	0	13.459
Independent Variables – Firm-specific Variables				
Non-debt tax shield (NDS)	0.045	0.044	0.000	0.991
Size (S)	9.951	1.115	0.000	17.111
Net trade credit (NTC)[6]	0.028	1.131	–149.854	211.753
Independent Variables – Macroeconomic Variable				
Term spread (Term Spread)	0.007	0.016	–0.028	0.024
Independent Variables – News Variable				
Economic policy uncertainty index	135.471	37.945	81.349	191.285

[5] Descriptive statistics is for the final database without outliers, with 70,734 observations.

[6] This variable serves solely for verification purposes and is excluded from the primary model due to its lack of significance under the DPF estimator.

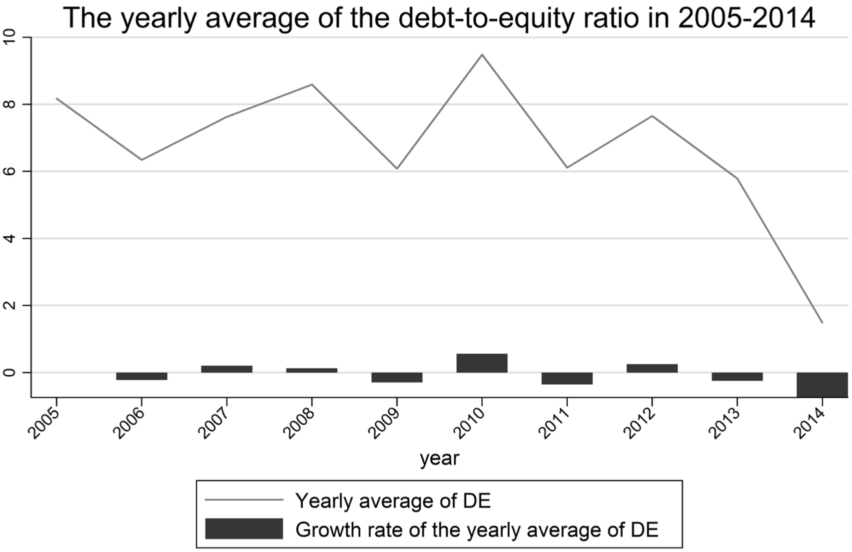


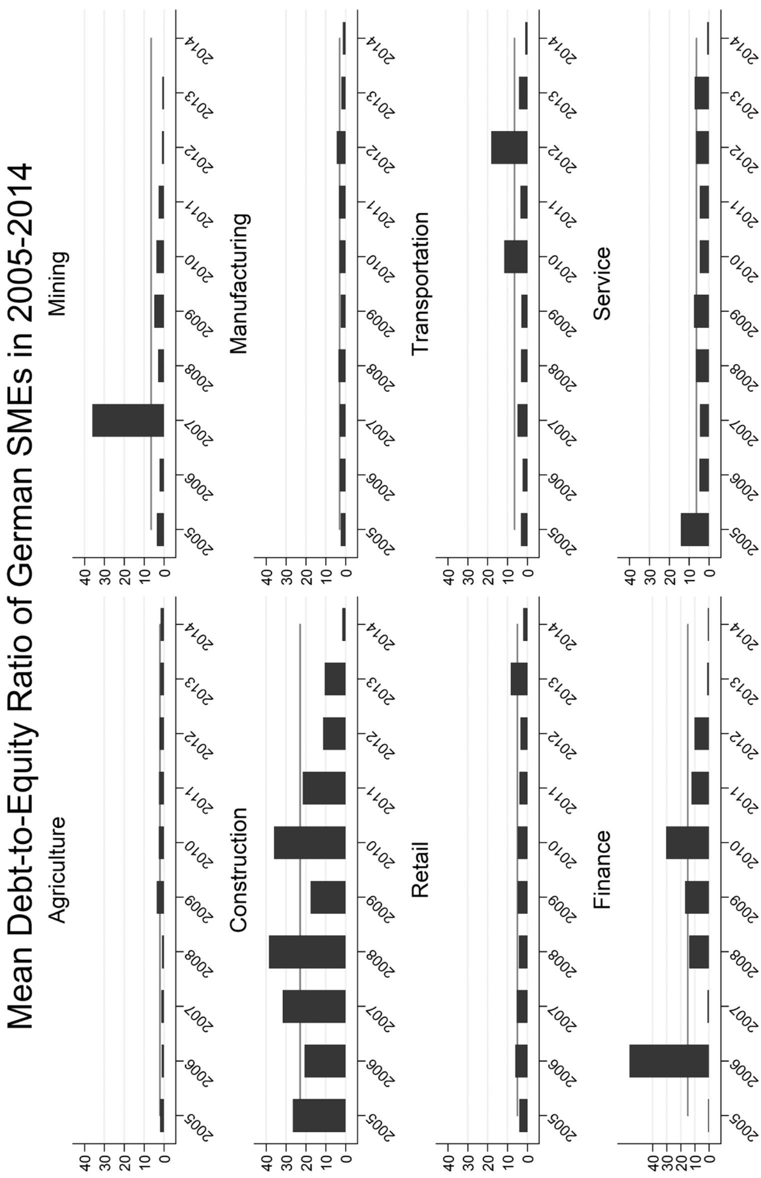
Figure 1: Overall yearly mean of the debt-to-equity ratio of SMEs in Germany

The debt-to-equity ratio is frequently 0, with 18,216 observations, indicating that more than 25 % of firms have no debt. This may reflect limited access to debt for some German SMEs, or these firms could be receiving subsidies for innovative ideas or financed through trade credit.

The view from the dynamic perspective (as depicted in Figure 1) shows that the overall yearly means of the debt-to-equity ratio were increasing before 2008. In 2010, the ratio reached its peak and dropped down again in 2011. In 2014, there was a sharp decline in the overall debt financing of SMEs.

To understand the factors behind these changes, we analyze the trend lines of debt-to-equity ratios across industries (refer to Figure 2).

Overall, the construction and finance industries show notably higher leverage compared to other sectors. In 2009, the sharp decrease in SMEs' debt financing in the construction industry contributed to the overall decline in SMEs' debt financing in Germany, reflecting increased risk aversion due to the crisis.



Note(s): The grey line represents the industry's average debt-to-equity ratio.

Figure 2: Debt-to-equity ratio of German SMEs per industry from 2005 to 2014

Table 3

Sample composition by industry (by SIC classification)

Industry	*Industry Abbreviation*	*Freq. (after trimming)*	*%*
Agriculture, forestry, and fishing	Agriculture	731	1.03
Mining and quarrying	Mining	159	0.22
Construction	Construction	8,913	12.60
Manufacturing	Manufacturing	21,109	29.84
Wholesale and retail trade	Retail	15,418	21.79
Transportation and public utilities	Transportation	11,407	16.12
Finance, insurance and real estate	Finance	480	0.68
Service and public administration	Service	12,512	17.68
Total		70,734	100.00

Table 3 outlines the sample composition after outliers were removed, indicating that the cleaned dataset comprises SMEs from various industries classified under SIC. Manufacturing represents the largest share of observations (30 %), followed by wholesale and retail trade (22 %), service and public administration (18 %), among others.

2. *Model and methodology*

Our hypothesis of interest for individual firms is that the debt-to-equity ratio is determined by the existing debt-to-equity ratio, non-debt tax shield, and size. We choose these independent variables as they are recognized in the literature as determinants of capital structure, and they can be addressed by economic policy tools.[7]

We build the firm-level model for all SMEs irrespective of their industry belongingness as follows:

$$DE_{i,t} = \alpha_0 + \alpha_1 DE_{i,\,t-1} + \alpha_2 NDS_{i,t} + \alpha_3 s_{i,t} + c_{i,t} + u_i \tag{1}$$

Where DE is the debt-to-equity ratio, i is firm index, t stands for time, NDS is the non-debt tax shield, s is size, α_0, α_0, α_0 are the coefficients and u_i is the innovation.

[7] How and which policy tools can be used is discussed in the results part of this paper.

The unobserved heterogeneity $c_{i,t}$ is used only by the DPF estimator, and:

$$c_{i,t} = \alpha_6 \overline{DE}_{industry,\ i,t-1} + \alpha_7 \overline{NDS}_{industry,i,t} + \alpha_8 \overline{s}_{industry,i,t}$$

Where bars denote the overall time-series averages of the exogenous variables.

We propose that in each industry, a company's debt-to-equity ratio is determined by the microeconomic variables in equation 1 and macroeconomic conditions. The DPF estimator also uses the averages of the microeconomic and macroeconomic conditions and the SME's first value of *DE*.

The proposed model for leverage ratios for firms in each industry is:

$$\begin{aligned} DE_{industry,\ i,t} = {} & \alpha_0 + \alpha_1 DE_{industry,\ i,\ t-1} + \alpha_2 NDS_{industry,\ i,t} + \varepsilon_3 s_{industry,\ i,t} \\ & + \alpha_4 TS_{t-1} + \alpha_5 EUI_{t-1} + c_{i,t} + u_{it} \end{aligned} \tag{2}$$

Where, TS_{t-1} is term spread in previous period,

EUI_{t-1} is economic uncertainty index in previous period,

The unobserved heterogeneity $c_{i,t}$ is used only by the DPF estimator, and:

$$\begin{aligned} c_{i,t} = {} & \alpha_6 \overline{DE}_{industry,\ i,t-1} + \alpha_7 \overline{NDS}_{industry,i,t} + \alpha_8 \overline{s}_{industry,i,t} \\ & + \alpha_9 \overline{TS}_{t-1} + \alpha_{10} \overline{EUI}_{t-1}. \end{aligned}$$

Where bars denote overall time-series averages of the exogenous variables in each of 8 SIC industries.

In this article, we utilize panel estimation methods with German SMEs data. We employ standard estimators like the Blundell-Bond estimator, along with a more precise and less biased approach: the Dynamic Panel Fractional (DPF) estimator.

a) Dynamic Panel Fractional (DPF) Estimator

The authors of the dynamic panel fractional estimator (DPF), *Elsas/Florysiak* (2015), based on the Monte Carlo study, demonstrate that the DPF has higher precision of estimation for the speed of capital structure adjustment than fixed effects models and the instrumental variables (IV)-based estimators: GMM Blundell-Bond estimator, long difference estimator, and Least-squares dummy variable estimator. Moreover, the study by *Elsas/Florysiak* (2015) theoretically proves that the commonly used estimators produce biased estimates of the speed of capital structure adjustment, while the DPF estimator does not. Thus, we apply a left-censored version of the dynamic panel fractional (DPF) estimator to the speed of capital structure adjustment of German SMEs and compare the results to those produced by other methods.

The special characteristic of the DPF estimator is that it is not limited to fractional dependent variables. The DPF estimator can also be applied to nonfractional data, as it can transform the debt-to-equity ratio to a latent variable with values between 0 and 1 (or by researcher-defined upper bound) and achieves higher precision of estimations (*Elsas/Florysiak* 2015). *Elsas/Florysiak* (2015) apply the DPF estimator to a nonfractional dependent variable, and the DPF estimator remains the best-performing estimator between the Blundell-Bond, LSDVC, and long difference estimator. Besides, the estimates of the nonfractional dependent variable by the DPF estimator are not biased. Due to this, we apply the DPF estimator to the nonfractional debt-to-equity ratio. Additionally, we apply the right-censored DPF estimator to the debt-to-equity ratios of the equity-financed firms to ensure the correctness of the model for the subgroup of the equity-financed firms (for which DE ≤ 1).

To address the fractional nature of the dependent variable, DPF utilizes a latent, i.e., unobserved variable approach. DPF employs a censored Tobit specification, which is double censored for fractional dependent variables, accommodating corner observations. In other words, the dependent variable remains upper bound (UB) for the cases when the latent variable is taking a value more than the upper bound and equals 0 when the latent variable is less than 0; in the [0, *UB*] interval, the dependent variable is equalized to the latent variable.

(4) $$y_{it} = \begin{cases} UB & for\ y_{it}^{*} \geq UB \\ y_{it}^{*} & for\ y_{it}^{*} \in (0, UB) \\ 0 & for\ y_{it}^{*} \leq 0 \end{cases}$$

The unobserved variable (y_{it}^{*}) is implied by lagged dependent variable ($y_{i,t-1}$), a vector of exogenous regressors (Z_{it}),[8] and a normally distributed error term, along with unobserved heterogeneity (c_i).[9]

(5) $$y_{it}^{*} = Z_{it}\varphi + \rho y_{i,t-1} + c_i + u_{it}$$

Where the error term u_{it} is normally distributed $u_{it} \sim N(0, \sigma_u^2)$.

As we follow *Elsas/Florysiak* (2015), we assume that the fixed effects in the DPF model have the distribution: $c_i = a_0 + a_1 y_{i,0} + \bar{Z}_i a_2 + a_i$, where $a_i \sim N(0, \sigma_a^2)$, In

[8] In this study, this matrix includes firm-specific variables such as size and non-debt tax shield. For the industry-level and macro-level capital structure models, it also includes lagged term spread and lagged economic policy uncertainty index.The error term is normally distributed with 0 mean.

[9] Unobserved heterogeneity refers to the presence of unobserved variability or nonuniformity in the data.

other words, fixed effects depend on the time series averages of exogenous regressors and the initial leverage. The initial leverage is:

$$\text{(6)} \qquad y_{i,0} = \lambda\ (\acute{X}_{i,0}\gamma) + a_0 + \frac{1}{T}\sum_{t=0}^{T} \acute{X}_{i,t}\, a_2 + a_i + u_{i,0}\,.$$

Where we again follow *Elsas/Florysiak* (2015) and assume that for the initial leverage (at the beginning of the data generating process), $a_0 = 0.1$, $a_2 = -0{,}25$, $a_i \sim N(0{,}0.01)$, and $u_i \sim N(0{,}0.01)$. $Z_{it}\varphi = (\acute{X}_{i,0}\gamma)$, where λ is the true leverage, $\acute{X}_{i,0}$ is one of the exogenous regressors, and γ is the corresponding coefficient.[10]

DPF estimator is a Maximum Likelihood estimator. The resulting log likelihood function has the form:[11]

$$\text{(7)} \qquad L = \sum_{i=1}^{N} \log\left\{ \int_{-\infty}^{\infty} \left[\prod_{t=\tau_i}^{T_i} f_t\left(y_{i,t}\, | Z_{i,t}\, y_{i,t-1} \overline{Z}_i\, y_{i,0} a_i\,; \theta\right) \right] \frac{1}{\sigma_a} \varphi\left(\frac{a_i}{\sigma_a}\right) da_i \right\}$$

Where τ_i is the first and T_i is the last observation of the imbalanced data.

For the case when dependent variable is not fractional (such as debt-to-equity ratio) and has only one defined border (like DE, $0 < DE < \infty$) one can imply the lower boundary and leave the upper boundary as is or set it to the maximum value observed in the data. In this study, we set the upper boundary of the DPF estimator to the maximum value observed in our data.

IV. Results

1. *Firm-specific variables*

Before applying our model, we start our analysis by checking the nature of the debt-to-equity data. The results of the Breusch and Pagan Lagrange multiplier test for random effects suggest that the random effects model outperforms pooled OLS Hausman tests. This indicates that there are significant differences between German SMEs, thus we have individual effects (random effects). Nevertheless, random effects models like fixed effects model perform poorly for estimating the debt-to-equity ratio.

[10] For more details see the Monte Carlo simulation in *Elsas/Florysiak* (2015).

[11] For the calculations of the log likelihood function see the online appendix A of *Elsas/Florysiak* (2015).

Table 4

Firm-level model for debt-to-equity ratio

Model Variables	*Random Effects Model*	*Blundell Bond*	*Censored Tobit*	*DPF*
Lag DE	*0.5620**** (0.0032)	0.0159 (0.0225)	*0.6440**** (0.0051)	*0.0514**** (–0.0022)
NDS	*0.8460**** (0.1460)	–0.3400 (0.3620)	*0.8210**** (0.1310)	0.0939 (–0.0688)
Size	*–0.0219**** (0.0068)	–0.0541* (0.0277)	*–0.0115*** (0.0056)	0.0011 (0.0047)
For each ID the first entry of DE	---	---	---	0.0942 (0.0850)
Mean DE	---	---	---	*–0.0004**** (0.0001)
Mean NDS	---	---	---	*–0.0248**** (0.0033)
Mean s	--- ---	--- ---	--- ---	*0.2058**** (0.0063)
Const	*0.5750**** (0.0689)	1.3850*** (0.2800)	*0.3720**** (0.0579)	*1.0617**** (0.1051)
Observations	49,974	49,974	49,974	49,974
Number of firms	13,051	13,051	13,051	13,051
R-squared within	0.0000	---	---	---
R-squared between	0.5210	---	---	---
R-squared overall	0.4778	---	---	---
sigma_u	0.6850	---	---	*0.2966****
sigma_e	0.8200	---	---	*0.1917****
Rho	0.4110	---	---	0.7054
Valid Moment Conditions	---	No	---	---

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ Standard errors are in parenthesis.

The moment conditions for the Blundell Bond GMM estimator are not valid here.

In Table 4, we document coefficient estimates of different methods for our firm-level model of the debt-to-equity ratio described in equation 1. The Blundell-Bond GMM estimator, developed by *Blundell/Bond* (1998), overcomes the endogeneity problem and is less biased compared to fixed effects and random effects models. It yielded significant results for our model with the firm variables: non-debt tax shield and firm size, with a corresponding speed of capital structure adjustment of 90 %. However, due to the potential for overfitting endogenous variables, the Blundell-Bond GMM estimator may introduce bias. To validate the results, we check the validity of the instruments for the Blundell-Bond model at the firm-level and find that the instruments are not valid in this context. To address this, we utilize the unbiased DPF estimator for more precise results. The coefficients of our firm-level model remain significant when assessed by the DPF estimator, affirming the validity of our model.

As evident from Table 4, the results of the Blundell-Bond estimator should be disregarded due to invalid moment conditions. However, in the firm-level model presented in Table 4, the coefficients of the non-debt tax shield (NDS) are statistically significant in random effects and censored Tobit estimations, and the means of NDSs are statistically significant in DPF estimations. Similarly, the size variable exhibits statistical significance across all models. Furthermore, the lagged debt-to-equity ratio is statistically significant in all models. In conclusion, NDS, size, and lagged DE significantly influence debt financing decisions.

The robustness tests discussed in the online appendix of this paper, confirm that our model of German SMEs, which includes NDS and size, performs slightly better than models incorporating other firm-specific variables such as tangibility and profitability.

Table 5

Panel a: Industry-specific model – Blundell Bond estimator

	(1) *Agriculture*	(2) *Mining*	(3) *Construction*	(4) *Manufacturing*	(5) *Retail*	(6) *Transportation*	(7) *Finance*	(8) *Services*
Lag DE	*0.7010**** (0.0021)	*0.6283**** (0.0114)	*−0.0403**** (0.0103)	*0.0160* (0.0183)	*0.0230* (0.0242)	*0.0088* (0.0293)	*0.4943**** (0.0004)	*0.0070* (0.0217)
NDS	*−4.9742**** (0.3463)	*9.3988**** (0.6577)	*−0.1948* (1.9032)	*−1.0457** (0.6285)	*−0.2142* (0.3306)	*−1.7345* (1.1149)	*13.4694**** (0.1398)	*−0.0064* (0.3871)
size	*−0.3294**** (0.0279)	*−0.1001* (0.0794)	*−0.0478* (0.0661)	*−0.1794**** (0.0464)	*0.0179* (0.0460)	*−0.0187* (0.0353)	*−0.0842**** (0.0047)	*−0.0678* (0.0444)
Lag Term Spread	*1.9545**** (0.2775)	*14.1222**** (0.2479)	*0.0720* (0.4709)	*0.7487**** (0.2870)	*−0.1927* (0.3440)	*0.5425* (0.3481)	*−2.5909**** (0.0599)	*0.4600* (0.3234)
Lag Uncertainty Index	*0.0008**** (0.0001)	*−0.0066**** (0.0003)	*−0.0015**** (0.0004)	*−0.0004** (0.0002)	*−0.0001* (0.0003)	*0.0001* (0.0002)	*0.0010**** (0.0001)	*0.0001* (0.0002)
Constant	*3.3611**** (0.2530)	*1.6477*** (0.7440)	*2.0522**** (0.6437)	*2.7092**** (0.4817)	*0.5836* (0.4814)	*0.9866*** (0.3838)	*0.7824**** (0.0430)	*1.2146**** (0.4153)
Observations	494	118	6,414	14,407	11,035	8,481	333	8,690
Number of firms	152	28	1594	4049	2783	1912	96	2435
Valid moment conditions[12]	No	No	Yes (lag2)	Yes (lag2)	Yes (lag1)	Yes (lag1)	No	Yes (lag1)

Note(s): Standard errors in parenthesis; *** p < 0.01, ** p< 0.05, * p < 0.1

[12] The moment condition here is "no serial correlation in idiosyncratic errors". The model is estimated with robust errors. Here we use robust errors and correspondingly estimate differenced equations, as the GMM two-step standard errors are biased in all industry models.

Table 5

Panel b: Industry-specific model – censored Tobit[13]

	(1) *Agriculture*	(2) *Mining*	(3) *Construction*	(4) *Manufacturing*	(5) *Retail*	(6) *Transportation*	(7) *Finance*	(8) *Services*
Lag DE	*0.6901**** (0.1529)	*0.7216**** (0.2635)	*0.5853**** (0.0775)	*0.6422**** (0.0295)	*0.5408**** (0.0530)	*0.6082**** (0.0762)	*0.6135**** (0.1728)	*0.6071**** (0.0330)
NDS	*–1.1159* (1.9774)	*2.9625* (3.2751)	*1.6303* (1.1966)	*1.7697**** (0.3693)	*1.8257**** (0.6086)	*2.5908**** (0.7699)	*7.4793*** (3.2511)	*1.1520**** (0.4208)
size	*–0.0522* (0.0975)	*–0.2824* (0.3779)	*0.0619*** (0.0258)	*–0.1387**** (0.0195)	*–0.0431** (0.0249)	*–0.0481** (0.0257)	*0.0933* (0.1059)	*–0.0312** (0.0187)
Lag Term Spread	*1.6494* (2.5156)	*13.4576** (7.1734)	*1.3407* (1.1031)	*1.3425* (0.9207)	*1.6184* (1.0935)	*–0.3414* (1.0216)	*–12.3409**** (4.0611)	*0.3254* (1.1585)
Lag Uncertainty Index	*–0.0005* (0.0016)	*–0.0033* (0.0043)	*–0.0011*** (0.0006)	*–0.0002* (0.0004)	*–0.0009** (0.0006)	*–0.0001* (0.0004)	*0.0022* (0.0024)	*–0.0008* (0.0005)
Constant	*0.7829* (0.9674)	*3.2964* (4.3589)	*–0.1513* (0.2716)	*1.3649**** (0.2004)	*0.4771** (0.2792)	*0.3442* (0.2696)	*–1.6542* (1.1061)	*0.1542* (0.1910)
Sigma_u	0.6976** (0.3465)	1.1038** (0.4355)	0.9531*** (0.1956)	0.6709*** (0.0540)	1.3194*** (0.1588)	0.9573*** (0.1952)	1.4225*** (0.3799)	0.9566*** (0.0902)
Sigma_e	0.5777*** (0.1642)	0.8569*** (0.2546)	1.0298*** (0.0846)	1.0070*** (0.0440)	1.0674*** (0.0594)	0.9719*** (0.0549)	1.2554*** (0.2646)	1.0534*** (0.0716)
rho	0.5470	0.1000	0.0000	0.0000	0.5528	0.4962	0.5312	0.0000
Observations	494	118	6,414	14,407	11,035	8,481	333	8,690
Number of firms	152	28	1,594	4,049	2,783	1,912	96	2,435

Note(s): Standard errors in parenthesis; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[13] The Tobit model is a left censored Tobit model at minimum DE, i.e. at 0. For highest precision possible, the model is estimated with bootstrapping method.

Table 5

Panel c: Industry-specific model – DPF estimator

	(1) Agriculture	(2) Mining	(3) Construction	(4) Manufacturing	(5) Retail	(6) Transportation	(7) Finance	(8) Services
Lag DE	*0.2292**** (0.0278)	*0.6654**** (0.0828)	*0.1121**** (0.0068)	*0.1426**** (0.0052)	*0.0926**** (0.0055)	*0.1137**** (0.0058)	*0.1702**** (0.0417)	*0.1118**** (0.0063)
NDS	*0.5363* (0.7011)	*0.9559* (1.7720)	*−0.0244* (0.3652)	*−0.4649*** (0.2069)	*0.4390*** (0.2190)	*−0.2562* (0.1742)	*−0.1004* (1.8411)	*−0.0799* (0.1982)
size	*−0.0004* (0.0300)	*−0.0421* (0.1839)	*0.0026* (0.0164)	*−0.0382*** (0.0149)	*0.07100**** (0.0185)	*0.0101* (0.0141)	*−0.0776* (0.0527)	*0.0077* (0.0134)
Lag Term Spread	*−0.0674* (0.5715)	*0.0342* (2.2599)	*0.2452* (0.3492)	*0.2194* (0.2329)	*0.5431** (0.3006)	*0.2581* (0.2409)	*0.4971* (1.9552)	*0.1837* (0.2886)
Lag Uncertainty Index	*0.0001* (0.0003)	*0.0004* (0.0010)	*−0.0008**** (0.0002)	*−0.0010**** (0.0001)	*−0.0010**** (0.0001)	*−0.0001* (0.0001)	*0.0003* (0.0009)	*−0.0005**** (0.0001)
For each ID the first DE	*−0.2178**** (0.0250)	*−0.1238**** (0.0392)	*−0.0009* (0.0084)	*−0.0610**** (0.0061)	*−0.0967**** (0.0076)	*−0.0683**** (0.0116)	*−0.0292* (0.0287)	*−0.0924**** (0.0081)
mean Lag DE	*0.5090**** (0.0562)	*0.2953**** (0.0797)	*0.3470**** (0.0172)	*0.4249**** (0.0122)	*0.5811**** (0.0155)	*0.5512**** (0.0240)	*0.4830**** (0.0887)	*0.4455**** (0.0160)
mean NDS	*0.4816* (0.7936)	*−0.9515* (1.8827)	*2.5714**** (0.5038)	*2.1273**** (0.3015)	*0.7877*** (0.3961)	*0.5520*** (0.2250)	*1.5178* (2.2965)	*0.8358**** (0.3202)
mean s	*−0.0118* (0.0328)	*0.0311* (0.1860)	*0.0687*** (0.0312)	*−0.0187* (0.0172)	*−0.0829**** (0.0201)	*−0.0088* (0.0163)	*0.1470*** (0.0639)	*−0.0230* (0.0148)
Mean Lag Term Spread	*−1.8878* (2.2899)	*−12.3582* (7.6526)	*−2.0002* (2.0249)	*2.0809*** (1.0561)	*−0.6725* (1.5531)	*4.1296**** (1.5801)	*−18.3979*** (8.0860)	*−0.0113* (1.4109)

(continue next page)

(Table 5 continued)

	(1) Agriculture	(2) Mining	(3) Construction	(4) Manufacturing	(5) Retail	(6) Transportation	(7) Finance	(8) Services
mean Lag Uncertainty Index	*0.0005*	*0.0056***	*−0.0007*	*0.0013****	*0.0007*	*−0.0012***	*0.0022*	*0.0006*
	(0.0007)	(0.0027)	(0.0007)	(0.0004)	(0.0005)	(0.0005)	(0.0027)	(0.0004)
Constant	*0.1866*	*−0.6232*	*−0.3179*	*0.4778****	*0.0246*	*0.0583*	*−1.1261***	*−0.0079*
	(0.1465)	(0.4526)	(0.3185)	(0.1063)	(0.1100)	(0.1103)	(0.5358)	(0.0792)
Sigma_u	0.2449***	0.0000	0.4753***	0.3826***	0.4775***	0.3697***	0.4409***	0.4553***
	(0.0199)	(0.0691)	(0.0122)	(0.0072)	(0.0117)	(0.010)	(0.0594)	(0.0119)
Sigma_e	0.14806***	0.2726***	0.2885***	0.3115***	0.3279***	0.2622***	0.3615***	0.2942***
	(0.0065)	(0.0256)	(0.0048)	(0.0032)	(0.0042)	(0.0033)	(0.0273)	(0.0039)
rho	0.6233	0.0000	0.6223	0.5512	0.5929	0.5850	0.5495	0.6075
Observations	494	118	6,414	14,407	11,035	8,481	333	8,690
Number of firms	152	28	1,594	4,049	2,783	1,912	96	2,435
Log Likelihood	12.40	−34.83	−2715	−7504	−5448	−3423	−182.0	−4362
RMSE	0.2615	0.3018	0.2914	*0.0485*	*0.0067*	0.3281	0.3608	0.2932

Note(s): Standard errors in parenthesis*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5 presents the results of the debt-to-equity ratio model at the industry level. While we provide Blundell-Bond estimation results, we do not present GMM two-step estimation results due to unmet moment conditions. Panel a of Table 5 displays the estimation results of a differenced model with robust errors, where many model coefficients are statistically significant. Panel b presents the censored Tobit estimation, and panel c shows the DPF estimation. To ensure reliable statistical inference with an insufficient sample size, we utilize bootstrap-based sample augmentation mechanisms for the panel-censored Tobit estimations.

The lagged debt-to-equity ratio exhibits statistically significant coefficients across all industries in both estimations on panels b and c, suggesting a robust autocorrelation in the dependent variable over time. Furthermore, the industry means of the lagged debt-to-equity ratio, incorporated in the DPF estimator on panel c, consistently demonstrate statistical significance.

In Table 5, in the censored Tobit estimations on panel b, the coefficients of the non-debt tax shield are statistically significant in five out of eight industries, namely Manufacturing, Retail, Transportation, Finance, and Service industries. It's noteworthy that the censored Tobit model solely reveals direct NDS effects. Table 5, panel c provides a more detailed perspective from the DPF estimation.

Panel c of Table 5 presents the DPF estimation of the industry-specific model. NDS or time-series averages of NDS have statistically significant coefficients in 5 out of 8 industries: manufacturing, retail, construction, transportation, and service. In two of these five industries, manufacturing, and retail, the coefficients of NDS are statistically significant, suggesting that the last period NDS is a significant predictor of DE in these industries.

The industry panel means NDS influences financing decisions (debt-to-equity ratio) in 5 industries: construction, manufacturing, retail, transportation, and service industries. This indicates that the industry average debt tax shield plays a role in shaping financing decisions in these 5 industries, and NDS-related policies are effective for companies in these sectors. However, NDS-related policies are unlikely to influence the financing decisions of companies in the other 3 industries: agricultural, mining, and financial services industries. This lack of impact on financial services firms is expected, given their indifference to a non-debt tax shield. However, it serves as a significant indicator for policymakers regarding agricultural companies. Policymakers should explore alternative channels to influence the financing decisions of agricultural firms, as NDS-related policies are unlikely to be effective in this sector.

Table 5 reveals that capital structure is sensitive to the non-debt tax shield in certain industries, implying that tax policies related to the non-debt tax shield can influence debt financing decisions. It would be valuable to compare these findings with studies on SMEs, such as *Daskalakis/Psillaki* (2008) and *Matias/*

Serrasqueiro (2017) which also found a statistically significant influence of the non-debt tax shield on leverage. Moreover, our analysis delves deeper by identifying the specific industries where this effect occurs. Without this industry-level examination, we might have overlooked the fact that policies related to the non-debt tax shield are unlikely to significantly impact the agriculture industry, highlighting the importance of considering industry variations. We corroborate these differences across industries through ANOVA hypothesis testing of the various means of debt-to-equity ratio in each industry.

The signs of the relationship and the expected reaction of the debt-to-equity ratio to changes in the non-debt tax shield vary across industries, as highlighted in our research.

In Table 5, panel b, we observe that coefficients of the non-debt tax shield are negative for four industries, while positive for others such as mining, retail, and transportation. This implies that in response to an increase in non-debt tax shields, leverage might increase in these specific industries. We attribute this discrepancy to the industry effect, which provides different incentives for firms in various sectors, leading to divergent reactions to changes in tax policy.

Our findings in Table 5, panel c, indicate a statistically significant and positive relationship between non-debt tax shields and corporate debt levels within the retail industry. Additionally, the means of non-debt tax shields are statistically significant and positively related to the debt-to-equity ratio across the construction, manufacturing, retail, transportation, and service industries. These results suggest that debt financing in the construction, retail, transportation, and service sectors is likely to increase in response to tax policies that encourage the incorporation of non-debt tax shields.

Our result in Table 5, panel c, shows that a non-debt tax shield is statistically significantly and positively related to the corporate debt level in the retail industry, and the average of a non-debt tax shield is also statistically significant, positively related to the debt-to-equity ratio, in the construction, manufacturing, retail, transport, and service industries. These findings infer that debt financing of construction, retail, transport, and service industries will increase in response to tax policy that promotes incorporating a non-debt tax shield. In the manufacturing industry (column 4), the positive coefficient of mean NDS has a larger magnitude than the negative NDS coefficient. Leading to the conclusion that debt financing can decrease or increase in response to tax policy that promotes incorporating a non-debt tax shield, the result depends on how much the change in NDS changes the industry panel mean of the NDS. If the change of the company's NDS changes the industry mean of NDS by more than 0.2185 points (which is a fraction of NDS's coefficient and Mean NDS coefficient, 0.46485/2.12734), then the debt-to-equity ratio of the company will rise in response to increased NDS of the company; otherwise, DE will decrease in response to increased NDS. Hence, the impact of tax policies promoting the incorporation of non-debt tax shields in the manufacturing industry appears ambiguous. Our findings indicate a mixed effect, with the relationship being positive in some instances and negative in others. As the coefficients of other industries are statistically insignificant, we can assume that the change in NDS will not have a significant influence on the debt-to-equity ratio of the companies in those industries.

In general, the government should apply a tax policy that promotes SME investments without causing high indebtedness and inefficiency. This entails incentivizing reinvestment of earnings and encouraging debt only when it does not lead to excessive indebtedness. It is prudent to compare the debt-to-equity ratios (DE) of industries against acceptable, healthy levels specific to each industry and address them accordingly.

As a rule of thumb, a DE of less than two is considered favorable. However, for industries requiring minimal capital, a DE of up to 1.5 is deemed appropriate. Conversely, industries needing substantial capital may have a healthy average ratio value of up to 2.5. An exception is the finance industry, where higher than "healthy" DE levels indicate significant external financing, posing increased risk if debt levels rise further.

Given our finding that the debt-to-equity ratio is responsive to non-debt tax shields, policymakers have a potential lever to increase the leverage of small firms. However, caution is warranted to prevent DE from exceeding healthy industry levels and to avoid unnecessary accumulation of risk. A non-debt tax shield-related tax policy can indeed impact the leverage of German SMEs. Therefore, our first policy implication is as follows:

- Incentives for non-debt tax shields can be implemented when higher debt financing of SMEs is necessary, and the current debt-to-equity ratio (DE) is below a "healthy level" of DE.
- Tax policies aimed at increasing non-debt tax shields would directly increase the debt-to-equity ratio (DE) in the retail industry, while indirect effects would be observed in the construction, manufacturing, retail, transportation, and service industries. However, the impact of non-debt tax shield changes on DE in the manufacturing industry remains ambiguous.

By presenting equations for both firm and industry levels, this paper provides insights into how adjustments in tax policies across various industries can influence changes in SMEs' capital structure. It elucidates that a higher non-debt tax shield could yield diverse effects across different industries, thereby averting the fallacy of drawing conclusions that are applicable only to certain industries and not universally to all SMEs.

In the industry-level analysis presented in Table 5, Panel b, we observe that size, similar to NDS, exerts a statistically significant influence on leverage across all industries. The positive coefficients of size in Table 5, Panel b suggest that smaller SMEs tend to utilize more debt compared to their larger counterparts. Interestingly, the firm-level model excluding macro and news-based variables also indicates that smaller firms exhibit a tendency to take on more debt. This seemingly contradicts the trade-off theory, which suggests a negative relationship between size and DE. However, a deeper examination using the DPF estimator reveals nuanced insights. Table 5, panel b demonstrates that size remains a statistically significant variable in financial decision-making for five out of eight industries.

In panel c of Table 5, we observe significant coefficients of size in two industries: manufacturing and retail, indicating that company size influences financial decisions. Specifically, larger firms in the retail industry opt for higher leverage levels, whereas in the manufacturing industry, smaller firms tend to choose higher leverage levels. The DPF estimation provides further insights, revealing that industry time-series means of company sizes also significantly impact financing decisions in manufacturing, retail, and financial service companies. Larger SMEs in construction and financial services tend to take on more debt, whereas the opposite holds true for manufacturing companies. Regarding retail companies, the response of DE to NDS is ambiguous, although it is likely negative, as indicated by the need for the mean of NDS to change by over 1.16 (0.0829/0.0710) points for the effect of changed NDS to become positive.

2. *Macroeconomic effects*

The industry-level model is documented in Table 5. In panel c of Table 5, we observe that the coefficients of interest rate spread and economic policy uncertainty are statistically significant in several industries. These results suggest that the selected macro variables do influence industry leverages in some industries.

Macroeconomic effects on SMEs' leverage are visible at the industry level. In the firm-level model (equation 1), adding macro variables to firm-specific variables does not significantly improve our model, most probably because we do not control for the industry effects, as shown in the industry effects subsection. In the industry-specific model given in equation 2, we consider industry effects, and adding macro variables significantly improves the performance of the model.

This study highlights the significance of the term spread as a determinant of the capital structure of German SMEs. In Table 5, Panel c, we observe that the lagged term spread holds significance in the retail and transportation sectors.

Comparing our findings with previous studies focusing on SMEs and the role of the term spread in determining leverage, our results align with existing literature. In Table 5, Panel c, we observe a direct impact of the previous period's term spread on leverage in the retail sector. This suggests that retail SMEs tend to exhibit higher leverage following periods characterized by high term spreads. The influence of the average interest rate spread on DE is positive in manufacturing and transportation industries and negative in financial services industry. This negative relationship between term spread and leverage in the finance industry mirrors the findings of *Korajczyk/Levy* (2003).

As a lower debt-to-equity ratio signifies higher reinvestment, we draw our second policy implication:

- A higher term spread is associated with increased leverage in the retail industry in the following period.
- Increases in the average term spread of government bonds can lower the debt-to-equity ratio, prompting increased reinvestments by SMEs in the financial industry.
- Decreases in the average term spread of government bonds lead to higher debt-to-equity ratios in manufacturing and transportation companies.

We observe a statistically significant negative relationship between economic policy uncertainty and leverage in four industries. In Table 5, Panel c, the coefficients of the Uncertainty Index show significant negative signs in Construction, Manufacturing, and Retail, indicating their predictive value in these sectors. Our findings regarding the correlation between leverage and economic uncertainty align with those reported by *Graham* et al. (2015) and *Zhang* et al. (2015). Hereby we draw our third policy implication:

- In the aftermath of periods characterized by high economic uncertainty, SMEs in the construction, transportation, retail, and service industries tend to decrease their leverage.
- If economic uncertainty increases, resulting in higher average uncertainty, mining companies tend to increase their debt levels.

From the above findings, it is evident that policymakers should consider the effects of term spread and economic policy uncertainty when manipulating SME debt levels.

A novel insight from the industry-level model is that different SMEs adjust their leverage so that debt-to-equity ratios of companies within the same industry move in response to factors such as firm size, non-debt tax shield, last period's maturity risk premium (interest rate spread), and macroeconomic conditions, including tax code changes, macro news in newspapers, and economic uncertainty reflected in the policy uncertainty index. This finding aligns with the market timing theory, which suggests that capital structure adjusts based on market conditions.

A single policy intervention will not have a lasting effect on capital structure; therefore, it is important to understand how long SMEs will deviate from their target capital structure to accommodate endogenous market and policy-induced shocks. The adjustment speed of capital structure indicates the flexibility of SMEs' capital structures and the time it takes for them to readjust to their target capital structures under new circumstances. The speed of capital structure adjustment for German SMEs is presented in Table 6.

Table 6

Speed of adjustment (SOA) of capital structure in German SMEs

Estimation Methodology	*Firm-Level Model SOA*	*Half-lives+*
Fixed Effects Model	99.52 % (LagDE, NDS, s)	0.12 Year (around 1.5 Months)
Blundell Bond (GMM-SYS)	89.9 %*** (LagDE, NDS, s)	0.3 Years (4 Months)
Censored Tobit	99,9 %** (LagDE, NDS, s)	0,1 year (around 1,2 Months)
DPF	87,9 % (LagDE, NDS, s)	0,33 year (around 4 Months)

Note(s): +Half-life is time needed for the 50 % adjustment to the target after the shock to the error term (all forces not in the model). Half-lives are calculated by: log (0.5)/log (1 – SOA).

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

The estimated adjustment speed by the Censored Tobit estimator is 99.9 %, corresponding to a half-life of 1.2 months, meaning that it takes German SMEs 1.2 months to adjust 50 % to the target capital structure. This suggests that German SMEs will require approximately 2.4 months for full adjustment to their optimal capital structure under new circumstances. Policymakers can benefit from this information, knowing that SMEs need 2.4 months to return to their target leverage ratios. With this insight, policymakers will understand that after any market or policy shock, SMEs will react chaotically for 2.4 months before stabilizing at their new optimal capital structure, all else being equal.

The estimated adjustment speed by the DPF estimator is 87.9 %, corresponding to a half-life of 4 months, indicating that it takes German SMEs 4 months to adjust 50 % to the target capital structure. This implies that German SMEs will require approximately 8 months for full adjustment to their optimal capital structure under new circumstances. Policymakers can benefit from this information, understanding that SMEs need 8 months to return to their target leverage ratios. With this insight, policymakers will realize that after any market or policy shock, SMEs will react chaotically for 8 months before stabilizing at their new optimal capital structure, all else being equal. Hereby we draw our fourth policy implication:

- The utilization of policy tools in a single period will be effective for short-term adjustments of SMEs' capital structures. The effects of a one-period policy change might diminish after 8 months.

The speed of capital structure adjustment is essential information for investment decision-making at the right moment. Using the Censored Tobit estimator, we conclude that the capital structure of German SMEs adjusts by 99 % per year. This high speed indicates that SMEs adjust their capital structure very quickly, taking around 2.4 months to do so. This level of flexibility makes investment in German SMEs attractive. Additionally, the high speed of capital structure adjustment suggests that the developed banking sector supports SMEs in getting closer to their leverage target.

The DPF estimator provides us with additional insight. It reveals that the speed of capital adjustment in German SMEs is not as fast as indicated by the Censored Tobit estimator. This suggests that German SMEs are not as flexible as they could be. There is a need to improve financing opportunities for German SMEs, which would support them in overcoming challenging situations such as recessions or financial crises.

2. *Industry Effects*

We test industry effects by comparing the means of debt-to-equity ratios in different industries using an ANOVA test. The results of the ANOVA test are presented in Table 7.

Table 7

ANOVA hypothesis testing for different means of DE in different industries.

		Analysis of Variance			
Source	SS	df	MS	F	Prob> F
Between groups	2827643.6	8	353455.45	10.49	0.0000
Within groups	2.4574e+09	72912	33702.9919		
Total	2.4602e+09	72912	33738.0717		

Bartlett's test for equal variances: chi2(8) = 7.0e + 04 Prob > chi2 = 0.000

The ANOVA hypothesis test and Bartlett's test for equal variances show that the means of DE in different industries are significantly different, and the variances of DE ratios in different industries also differ.

As seen in Table 7, F-test suggests that the means of leverage ratios (DE) are statistically different across different industries.[14] This indicates that German SMEs leverage ratios are subject to statistically significant industry effects.

Even a visual graph analysis at first glance signals that SME capital structures in different industries must differ from one another (see Figure 1). On Figure 1, we observe that the real estate industry and financial industry have much higher leverage compared to other industries, while the service industry (consisting of the education industry, arts, entertainment and recreation industry, health care and social work industry) had a significantly lower debt-to-equity ratio. This visual check, together with the ANOVA results in Table 7, directly supports our hypothesis that industry influences the leverage decisions of SMEs. The visual analysis supports the argument by *Serrasqueiro* et al. (2011) that SMEs from the service industry might tend to have a lower debt-to-equity ratio. An additional ANOVA test that we conducted to determine if the mean debt-to-equity ratio of the service sector differs from the mean debt-to-equity ratios in other industries also suggested that the leverage of German SMEs in the service industry (including the education, arts, entertainment and recreation, and health care and social work sectors) differed from the leverage of SMEs in other industries.

These results are useful for taxation policymakers in creating tax incentives for SMEs interested in investments and development, as well as for banks that want to design funding products specific to SMEs from sectors that utilize debt for funding their investments.

The novel policy implication arising from the detected industry effects is that a one-size-fits-all approach is not optimal. Implementing a non-debt tax shield would encourage more equity investments in industries such as agriculture, mining, construction, and transportation, but would have a contrasting effect in industries like manufacturing, retail, or finance. Hereby we formulate our fifth policy implication:

– The same policy for all industries is not optimal, as industries react to conditions diversely.

[14] Means of debt to equity ratios in different years are not statistically different according to ANOVA hypothesis test. Thus, we reject the year effect. The interaction term of year and industry is also statistically insignificant.

V. Conclusion

In this paper, we investigate the capital structure decisions of German SMEs over a 10-year period, analyzing data from 13,051 SMEs. We examine both firm and industry-level factors and provide practical policy recommendations for different industries and SME groups.

Our study finds that the capital structure decisions of German SMEs are influenced by firm-specific variables such as size and the non-debt tax shield, as well as industry effects and macroeconomic factors. While our empirical findings generally support the trade-off theory, some industries may deviate from this expectation due to industry-specific effects on leverage. Notably, we identify a statistically significant relationship between leverage and SME size, consistent with the trade-off theory.

We observe a significant effect of the non-debt tax shield on German SMEs' capital structures across all industries, and the sign of the estimated effect changes depending on the industry. In manufacturing, retail, finance, and service industries, the non-debt tax shield is negatively related to leverage, aligning with the predictions of the trade-off theory. The inverse relationship is expected because firms using more depreciation as tax shields attempt to substitute tax benefits from not using debt financing. Consequently, policymakers can use a non-debt tax shield instead of other debt tax shields as a policy instrument to promote reinvestments and thus decrease the accumulated risk in SMEs from these industries. We find that, due to industry effects, the effect of the non-debt tax shield on leverage for agriculture, mining, construction, and transportation industries contradicts the expected sign according to trade-off theory. Industry-level analysis suggests selectively applying the policy instrument of the non-debt tax shield to certain industries. From our analysis of debt maturity structure, we also find that trade credit can serve as a policy tool for influencing debt maturity.

Though market conditions do not seem to directly determine leverage at the firm level, the industry-level analysis reveals that German SMEs are subject to the influence of market conditions. Results identify that the maturity risk premium (term spread) and uncertainty in the economy (policy uncertainty index) have a statistically important influence on the overall leverage of SMEs at the industry level.

This study draws several policy implications for German SMEs. Some of these recommendations are listed as follows:

1) Incentives of a non-debt tax shield can be applied if higher debt financing of SMEs is needed, and the current debt-to-equity ratio (DE) is lower than the "healthy level of DE".

2) Tax policies promoting higher non-debt tax shields (NDS) would increase the debt-to-equity ratio (DE) in the retail industry through a direct mechanism, and in the construction, manufacturing, transportation, and service industries through an indirect mechanism. The impact of changes in NDS on DE is ambiguous in the manufacturing industry.
3) A higher term spread on government bonds can trigger an increase in reinvestments by SMEs.[15]
4) In the period after an increase in economic uncertainty, SMEs' leverage is lower across industries.
5) A one-time policy use of policy tools will be effective for short-term adjustments of SMEs' capital structures. However, the effects of policy changes might dissipate after a period of 8 months.
6) The same policy for all industries is not optimal. Industries react to conditions diversely, and their reactions last for different periods.
7) To reduce borrowing costs and shorten the average maturity of SMEs' debt, policymakers can implement tax policies that encourage the use of trade credit.

For future research, it would be desirable to conduct the same analysis for periods during and after crises, or following the 2015 Investment Tax Act reform. Additionally, extending the model to include a business survey-based expectations variable, such as the KfW-ifo SME Barometer, could provide valuable insights, as it measures the mood in German SMEs and has been computed since 2004 from their business survey. Another intriguing research direction would involve analyzing panel data from multiple countries and incorporating institutional determinants into the model, as observed in Öztekin & Flannery (2012).

Online Appendix

Please refer to the online Appendix available on Zenodo via the following link: https://zenodo.org/records/11067693.

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