Financial Distress and the Effect of Leverage on German firms

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Abstract

This paper investigates whether publicly listed German firms experience a more pronounced decline in performance metrics—such as sales growth, stock returns, or profitability growth—during the Invasion of the Ukraine by Russia compared to their more conservatively financed counterparts. To test this, a pooled OLS regression model was applied and adjusted for fixed effects, with results drawn from three distinct periods of industry downturn: the migration crisis (2014–2016), the COVID-19 pandemic (2019–2021), and the Ukraine invasion (2021–2023). By examining these three periods, the study was able to explore the unique characteristics of each downturn and their varying impacts on firm performance metrics. Although the study did not find significant results in most cases, one notable finding is that highly leveraged firms that also operate in distressed industries experience significant and substantial cuts in sales growth.

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Resumo

O presente documento investiga se as empresas alemãs cotadas em bolsa registam um declínio mais pronunciado nos indicadores de desempenho - como o crescimento das vendas, a rendibilidade das acções ou o crescimento da rentabilidade - durante a invasão da Ucrânia pela Rússia, em comparação com as suas congéneres com financiamentos mais conservadores. Para testar isso, um modelo de regressão OLS agrupado foi aplicado e ajustado para efeitos fixos, com resultados extraídos de três períodos distintos de desaceleração da indústria: a crise migratória (2014-2016), a pandemia COVID-19 (2019-2021) e a invasão da Ucrânia (2021-2023). Ao examinar esses três períodos, o estudo foi capaz de explorar as caraterísticas únicas de cada crise e seus impactos variados nas métricas de desempenho da empresa. Embora o estudo não tenha encontrado resultados significativos na maioria dos casos, uma descoberta notável é que as empresas altamente alavancadas que também operam em indústrias em dificuldades experimentam cortes significativos e substanciais no crescimento das vendas.

Título: Dificuldades financeiras e o efeito do endividamento nas empresas alemãs

Autor: Tim Münster

Palavras-chave: Dificuldades financeiras, Desempenho da empresa, Quebras no sector

Table of Contents

List of Tables

Table of Figures

List of Abbreviations

MDA – Multivariate discriminant analysis

SME – Small and medium sized Enterprise

PP&E – Property, Plant and Equipment

VIF- Variance inflation factor

1 Introduction

For approximately two years, the German economic situation has been weakened, and a recovery in economic performance post-COVID remains a distant prospect. Typically, a slight increase in economic performance during one quarter is followed by a similar decline in the subsequent quarter. For instance, the economy grew by 0.2% at the beginning of the year, only to contract by 0.1% in the following quarter.

There are numerous reasons for this slow economic state. According to the ifo-Institute (2024), the primary cause is a structural crisis driven by challenges such as decarbonization, digitalization, demographic change, and the energy shock triggered during the Ukraine war. These challenges are diverse and primarily fall under the range of political action, but their impact is most acutely felt by the German economy and the companies operating within it. Established business models are under pressure, forcing firms to make strategic adjustments such as cost reductions or relocating production sites. The manufacturing sector, for example, is particularly affected by the rapidly aging population and the declining potential of labor force. Compared to other countries, Germany also has a higher proportion of companies operating in energy-intensive industries, which must contend with sharply rising energy costs. This includes sectors such as mechanical engineering and the already weakened automotive industry. Adding to the crisis is the investment and productivity stagnation of recent years. Looking back at the forecasts from 2019, current values are approximately 2% below those earlier estimates. One consequence of this heightened economic uncertainty is weak private investment activity and demand. This can be seen, among other indicators, in the private household savings rate, which is approximately 1% higher than the average of the ten years prior to the COVID-19 pandemic. The ifo-Institute (2024) further predicts that Germany's inflation-adjusted GDP will stagnate this year, indicating no immediate end to the crisis. It is evident that the current framework conditions for German companies are unfavorable, negatively impacting their performance. This could lead to an increased risk of insolvency, as weakened demand coupled with rising costs depletes liquidity buffers, making defaults on financial obligations more likely. In such situations, equity capital serves as a crisis buffer to absorb rising financial demands. Companies tend to consolidate during crises to withstand shocks from the macroeconomic environment. This trend can be observed not only in medium-sized enterprises but also among publicly listed companies. Compared to 2023, medium-sized companies have significantly increased their equity, a trend also evident in listed DAX companies (Creditreform, 2024). Previous studies support these observations, further demonstrating that firms with higher debt levels suffered

significant performance losses compared to their competitors when operating in financially weakened industries. For example, Opler and Titman (1994) highlighted this trend for U.S. firms during the period from 1972 to 1992.

This study seeks to examine whether the results observed in the past about the linkage between financial distress and corporate performance remain valid today. For that reason, this study will look at the most recent industry downturn, which was triggered by the outbreak of the Ukraine war and ultimately discuss and compare the findings to prior downturns such as the COVID-19 pandemic and the migration crisis. This results in the following research question:

"Are highly leveraged German firms more likely to experience performance losses compared to conservatively financed firms during the industry downturn triggered by the Ukraine war?"

To address this question, Chapter 2 will provide an overview of relevant topics from existing research. Chapter 3 will introduce the research methodology, followed by a descriptive discussion of the data and variables used in Chapter 4. Chapter 5 will present the results, which will be discussed in Chapter 6.

2 Literature Review

This section provides a comprehensive overview of theories, research and key concepts surrounding financial distress and leverage. The following will explore definitions, causes, costs and models to determine financial distress as well as the previous research that has contributed to the understanding of decision making on the optimal capital structure.

2.1 Definition of Financial Distress

Despite the extensive research conducted in this area, a consensus on a standardized definition of financial distress has yet to be reached. Consequently, each study employs its own definition to identify financially distressed corporations which leaves space to measurement errors and finally threatens the accuracy and reliability of research in this field. The rationale for this is that the application of varying definitions of financial distress enables researchers to categorize companies as financially distressed or not based on their own definition. Such inconsistencies in classification may result in the inclusion of non-distressed companies within the distressed group, or vice versa (Platt & Platt, 2006).

Lau (1987) utilized various indicators, such as layoffs, restructurings, and missed dividend payments, to assess the financial health of different firms. This approach facilitated a systematic classification of five distinct levels of financial condition. Hofer (1980) considers that a

negative net income, excluding special items, serves as a warning sign of financial distress, as it impairs a firm's ability to meet interest payments. Similarly, a low interest coverage ratio can signify financial difficulties, indicating that the company might struggle to pay both interest and principal, potentially resulting in insolvency over time (Asquith et al., 1994). Gordon (1971) shares this perspective, arguing that a decline in a corporation's earning capacity increases the likelihood that it will be unable to satisfy its interest and principal obligations, thus leading to financial distress. Furthermore, Whitaker (1999) describes the onset of financial distress as the initial year in which a firm's cash flow falls short of covering the current maturities of long-term debt. In addition, John, Lang, and Netter (1992) analyzed changes in equity prices or instances of negative EBIT as measures of financial distress.

Although there is no universally accepted definition of financial distress, it seems that the common understanding of the existent literature characterizes financial distress consistently as a condition in which a firm experiences difficulties in meeting its debt-related obligations, particularly the payment of interest or the repayment of principal. This state is often regarded as an early warning sign of more profound financial issues, indicating the potential for insolvency if the firm is unable to reverse the underlying problems that hinder its ability to service its debt.

2.2 Models of financial distress

Research into financial distress saw considerable progress in the 1960s when corporate debt and interest rates, as highlighted by Gordon (1971), surged to record levels. Concerns arose that firms might face failure, prompting increased attention to the issue. The absence of research and the tense economic climate led to the creation of the first models designed to predict financial distress. By now the academic research on business failure is extensive, and that is why only the most relevant and most used models will be discussed in this section.

The work proposed by Beaver (1966) constituted a notable advancement in the field of financial distress studies during this period, representing one of the earliest models in this area of research. Utilizing univariate discriminant analysis for selected ratios of both failed and non-failed firms, Beaver sought to uncover patterns that could predict corporate bankruptcy. His findings suggested that specific financial ratios could serve as early indicators of potential insolvency for at least five years prior to failure. Extending this work, Altman (1968) further refined the prediction model through the implementation of a multiple discriminant analysis (MDA), with the objective of identifying a set of ratios that could effectively predict corporate financial distress. For that purpose, he categorized variables into five standard categories of

ratios, namely those related to liquidity, profitability, leverage, solvency, and activity, as a result of their popularity and relevance in existing and forthcoming literature. Although the MDA approach has been the most widely used method in bankruptcy studies, Ohlson (1980) pointed out significant limitations, particularly related to assumptions of multivariate normality and variable independence. Therefore, Ohlson developed a model called the O-Score to overcome the limitations of the MDA approach, prioritizing robustness, simplicity and the minimization of estimation errors. To achieve this, he employed conditional logit analysis and considered a set of nine accounting variables. Zmijewski (1984) took a different approach by employing probit analysis to develop a three-variable prediction model. His model was designed to investigate the bias introduced by sample selection and data collection methods commonly used in failure prediction models at the time, which he successfully demonstrated through his methodology. Shumway (2001) follows a similar line of thinking, ensuring that his model avoids the selection bias frequently introduced when researchers focus solely on firm data from the year prior to bankruptcy, while neglecting data from healthy firms that could potentially become bankrupt in the future. That's why he developed a hazard model that takes all available information into account to determine each firm's bankruptcy risk at each point in time. The main advantage of Shumway's model is that it addresses the infrequent occurrence of distressed firm data, which static models struggle to handle without introducing biases, as they can only consider a single set of explanatory variables for each firm. Vassalou and Xing (2004) introduced a more recent approach by applying Merton's (1974) option pricing model to estimate default risk for individual firms, which they then used to analyze the relationship between default risk and equity returns. Their method shares similarities with the well-known KMV model, but key differences involve how asset volatility is calculated and the criteria for determining which capital instruments can be included in the firm's capital structure.

In a study conducted by Dimitras (et al., 1996) 47 studies on failure prediction models were reviewed, their analysis found that the discriminant analysis was the most widely applied technique, with solvency ratios being the most significant predictors, followed closely by profitability ratios. Balcaen and Ooghe (2006) reviewed 43 business failure prediction models and categorized them into four distinct groups. Most of the models that were used in the literature fell under MDA, followed closely by conditional probability models. The few remaining models were classified as univariate models and risk index models. Additionally, they also highlighted the increasing number of models grounded in option pricing theory and contingent claims as well as hazard models. A few years later, Jackson and Wood (2013) presented an overview of the frequency with which various prediction models are employed

and showed that hazard models and models based on option pricing theory indeed gained further popularity. The five most frequently utilized prediction models to that time were MDA, logit models, neural networks, contingent claims, and univariate analysis, listed in descending order of popularity. Ultimately, all models can be categorized into three categories (Bauer and Agarwal, 2014). Those are traditional models that are mainly based on accounting information (e.g. Altman, 1968), contingent claims-based models that use option price theory (e.g. Vassalou and Xing, 2004), and hazard models that follow a market approach (e.g. Shumway, 2001). For instance, Chava and Jarrow (2004) demonstrated that Shumway's (2001) hazard model surpassed both Altman's (1968) Z-Score and Zmijewski's (1984) model when they utilized an expanded database comprising firm data from 1962 to 1999 and incorporated industry effects in the hazard rate estimation. Their model accurately identified 74.4 percent of bankruptcies, compared to 63.2 percent for Altman's model and only 43.2 percent for Zmijewski's model. Also Ashraf et al. (2019) aimed to measure the efficacy of traditional distress prediction models by deploying them on firms in early and advanced stage of distress in an emerging market, namely Pakistan. Their results stated that the Altman Z-Score (1968) and Zmijewski's probit model (1984) were the most accurate models in terms of prediction accuracy, also indicating that the model by Altman (1968) is the most accurate model when the incorrect classification of distressed companies is seen more costly than the incorrect classification of stable firms. Ashraf et al. (2019) find these results to be in line with Wu et al. (2010) who evaluated five distress models applied to U.S. firms between 1980 and 2006. Furthermore, Altman et al. (2016) demonstrated that the revised Z"-Score model, introduced by Altman in 1983 as an extension of his original 1968 Z-Score model, continues to perform effectively with contemporary data in an international context. This highlights the enduring relevance of Altman's research even more than 50 years later.

2.3 Financial distress costs

Financial distress is generally perceived as costly because it often leads to decisions that can negatively affect debt holders or non-financial stakeholders, such as customers and suppliers, by increasing the costs associated with maintaining stakeholder relationships, and ultimately impacting firm value (Opler and Titman, 1994).

The literature distinguishes between two types of financial distress costs: direct and indirect. Warner (1977) explains that direct costs include fees paid to professionals such as lawyers, accountants, and other experts involved in the bankruptcy process. Additionally, there is the often-overlooked cost of managerial time spent on handling bankruptcy administration. He

further explains that for direct costs to occur, there must be significant transaction costs involved in negotiating and resolving disputes between claimholders. Put differently, direct bankruptcy costs would not exist in perfect or frictionless markets (Haugen and Senbet, 1978), that is because transferring ownership to creditors would be seamless and cost-free, meaning no expenses would arise in the event of a firm's failure (Higgins and Schall, 1975). Altman (1984) adopts the same distinction but expands it by noting that all administrative costs related to financial distress fall under direct costs. To measure them he defines direct costs as those explicitly paid by the debtor during the reorganization or liquidation process. His findings are consistent with Warner (1977), as direct costs averaged 2.8% of firm value (compared to Warner's 1.4%) five years before bankruptcy and 4.0% (versus Warner's 5.3%) just before bankruptcy. Altman's sample included retail and industrial firms that went bankrupt in the 1970s, while Warner's study focused on railroad companies that failed in the 1930s.

Indirect costs, according to Warner (1977), can arise from lost sales, diminished profits, or a firm's inability to access credit or issue new securities. He further highlights indirect costs that can also emerge from the bankruptcy process itself. Specifically, when a bankruptcy trustee is appointed to manage the company, there is uncertainty about whether the trustee will operate efficiently and with the goal of maximizing value. These costs, which would not arise without the trustee's involvement, create opportunity costs that can also be considered indirect costs of financial distress. Altman (1984), however, sees lost profits as the most important indirect cost when a company experiences financial distress. His findings reveal that indirect costs have a significantly greater impact on firm value than direct costs, accounting for an average of 8.1% of firm value three years before bankruptcy, rising to 10.5% in the year of bankruptcy. Commenting on these findings, Opler and Titman (1994) question whether the costs Altman (1984) considered should be attributed solely to financial distress, highlighting the significance of reverse causality. Specifically, the issue of whether the indirect costs arise from poor performance caused by financial distress, or if they stem from the factors that initially led to the financial distress - a distinction Altman (1984) does not address (Andrade and Kaplan, 1998). This is why Opler and Titman (1994) examined the indirect costs in a way to minimize the problem of reverse causality, they distinguish between three different indirect costs that result from financial distress. First, they categorize losses resulting from customers' unwillingness to deal with financially distressed firms as customer-driven costs. Similarly, they identify competitor-driven costs as those that arise when competitors exploit a firm's financial weakness through aggressive advertising or pricing strategies. Finally, costs associated with downsizing in response to financial distress are classified as manager-driven costs. Other significant indirect

costs include the loss of skilled workers and the inability to retain human capital, as noted by Baghai et al. (2021). Their study shows that skilled employees are more likely to leave a firm during periods of financial distress.

2.4 Causes of financial distress

Financial distress can arise from various factors, which have been extensively studied by researchers in the field. Asquith et al. (1991) identify three broad causes: industry downturns, high interest expenses, and poor firm operating performance relative to industry standards. Among these, firm performance is the most significant factor, contributing to 60% of the initial cash flow shortages, while high leverage accounts for 24%, and industry performance represents 16%. Likewise, Andrade and Kaplan (1998) identify high leverage, poor firm performance, and weak industry performance as key factors contributing to financial distress. In contrast to Asquith et al. (1991), they determine that high leverage is the leading cause of financial distress in firms. Additionally, they point out that the operating margins of their sample firms are significantly high, indicating that these firms would be considered healthier than the industry average if not for their substantial leverage. They also note that short-term interest rates can contribute to this distress. Furthermore, Denis and Denis (1995) found in their analysis of 29 leveraged recapitalizations that poor operating performance, largely due to industry-wide issues, plays a crucial role in driving firms into financial distress. They also discovered that distressed firms often structure their recapitalizations in a manner that leaves them more financially vulnerable than their non-distressed counterparts. The literature consistently identifies poor firm performance, high leverage, and weak industry performance as the primary drivers of financial distress. Nevertheless, different results show that it is not clear which of these factors is the most important cause.

2.5 The Role of Debt

As stated above, a high level of leverage is one of the main reasons why firms get into financial distress, that's why this section will investigate the mechanics and underlying theories to better understand what drives debt decisions and therefore optimal capital structure.

There was limited research on capital structure theory until Modigliani and Miller (1958) suggested that the value of a firm is unaffected by the amount of debt issued. Their later article (Modigliani and Miller, 1963) even showed that firm value is increased by the present value of the tax shield originated through debt financing. By the mid-1970s, the prevailing academic perspective was that the benefits of debt, particularly its tax advantages, needed to be weighed against the potential bankruptcy costs (Bradley et al., 1984). However, this perspective was

challenged when Miller (1977) argued that the tax benefits of corporate debt could be offset by personal-level tax disadvantages, ultimately driving market prices to equilibrium and suggesting the irrelevance of leverage. DeAngelo and Masulis (1980) expanded on this by examining whether leverage irrelevancy holds when debt-related costs, such as bankruptcy or agency costs, are considered. Their findings indicated that, despite significant leverage-related costs, corporate debt can still offer net tax advantages. In the end the firms decide on their optimal capital structure by the trade off between the tax advantage of debt and the various debt-related costs (Bradley et al., 1984).

Different view that is first suggested by Donaldson (1961) and was later modified by Myers and Majluf (1984) is the pecking order framework. The pecking order theory suggests that firms prefer internal financing over external sources, and if external financing is required, they prefer debt over equity, without aiming for a specific debt-to-value ratio (Myers and Majluf, 1984). The rationale behind this is rooted in two factors. First, external financing typically incurs costs such as administrative, underwriting, or potential underpricing of newly issued securities. However, asymmetric information introduces another concern: the opportunity cost of forgoing positive NPV investments if the firm avoids issuing securities due to these costs. This opportunity cost is avoided if the firm has sufficient internally generated cash. Secondly, if external funding is necessary, firms are better off issuing safer securities, like debt, before riskier ones like equity. Safer securities are less impacted by changes in value when the manager's inside information becomes public, whether that information is favorable or unfavorable, leading the securities to be either over- or underpriced. If securities are overpriced, investors would be reluctant to purchase equity as it would represent a poor investment. Conversely, when securities are underpriced, it is more advantageous for the firm to issue debt rather than equity. This dynamic ultimately makes debt the more attractive option for external financing (Myers, 1984).

A recent study on Portuguese firms (Serrasqueiro and Caetano, 2014) found that older Small and Medium-Sized Enterprises (SMEs) tend to use less debt, supporting the pecking order theory. In contrast, larger SMEs rely more on debt, aligning with both the trade-off theory and the pecking order theory. Overall, SMEs adjust their debt levels significantly towards an optimal ratio, consistent with the trade-off theory. The findings suggest that capital structure decisions of SMEs are not fully explained by either theory alone. Additionally, the study highlights the need for public financial support for smaller SMEs, as internal financing is often insufficient to cover all their activities. These findings align with other research, such as López-

Gracia and Sogorb-Mira (2008), which also concluded that the financing decisions of SMEs cannot be fully explained by a single theory. Their study supports the idea that SMEs generally follow a funding hierarchy, in line with the pecking order theory. Furthermore, their research suggests that larger trust is placed in SMEs that aim to achieve a target or optimal level of leverage, supporting the trade-off theory.

3 Data and Methodology

This section will provide an overview for the research design of this thesis' empirical analysis. This will include the research question, the data and sample selection process as well as the methodology used to apply the model. This paper aims to explore the relationship between financial distress and corporate performance, as established by Opler and Titman (1994), using recent data. Consequently, a significant portion of this section will adopt their approach to sample selection and methodology.

3.1 Data and Sample Selection

The data collection process was carried out in several steps, focusing on retrieving detailed information about both the company and the industry. For this analysis, firm- and industry-level data were sourced from Standard & Poor's COMPUSTAT and Refinitiv Workspace, covering three distinct periods of industry downturns. All three observation periods span close to three years each, with quarterly data extracted from income statement and balance sheet items to provide a more comprehensive dynamics of the data. Both the COVID-19 pandemic and Ukraine war observation periods were shortened by two months to avoid potential effects from overlapping data. The primary focus is on the period surrounding the Ukraine war, while the other two periods of industry downturn—the COVID-19 pandemic and the migration crisis—serve as comparison to enhance the analysis and deepen insights. The Russian invasion of Ukraine, which began on February 24th, 2022, not only marked a tragic event for humanity but also had devastating consequences for German industry. The halt in gas supplies from Russia led to gas shortages and further increased German electricity prices. This, among other factors, contributed to Germany's GDP growth being 2.4% lower compared to the previous year which therefore classifies this observation period as a period of industry downturn (lpb, 2022). Covering one year period to and one year following the invasion, the timespan observed starts at Q32021 and ends at Q42023. In parallel, the COVID-19 pandemic is examined within the timeframe of Q12019 to Q22021, and the migration crisis is analyzed for the years Q12014 to Q42016. To extract data on publicly listed companies in Germany, the respective Worldscope code was applied within Refinitiv Workspace to identify relevant ISINs. After adjusting for data

unavailability, delisting's, and mergers, the remaining ISINs were used to gather firm-level data, including balance sheet and income statement items, SIC codes, and stock data. The final sample selection followed a multiple criteria approach. For that Industries were classified using their three-digit SIC codes to enhance the precision and reliability of industry-level analysis, particularly for capturing within-industry effects. The following were excluded:

(1) Firms in the financial sector due to differing accounting practices in handling revenues and profits.
(2) Firms operating in industries with fewer than four companies, as smaller industry groups could skew results.
(3) Firms listing two or more industry segments in their annual reports, as this complicates accurate industry adjustments.
(4) Firms that lack the necessary data for analysis, such as ex ante leverage, stock returns, or sales growth in any quarter of the observation period.

This criterion, however, represents a slight deviation from the approach of Opler and Titman (1994), as adjusting for cross-sectional variation in ex-ante leverage had such a significant impact on the model's significance and explanatory power that this filter was ultimately not applied. After applying the specified criteria, the resulting dataset comprised 600 firm-quarters for the Ukraine war period, 590 firm-quarters for the COVID-19 pandemic, and 696 firm-quarters for the Migration crisis. All of these were used for the empirical analysis.

3.2 Research Model

This section introduces the pooled OLS regression model that has been used to predict firm performance, along with the variables that have been incorporated into the analysis. This analysis seeks to examine how leverage influences firm performance measures during periods of industry downturn. To achieve this, the following variables were selected as proxies for firm performance, again strongly inspired by the approach outlined by Opler and Titman (1994):

(1) **Sales Growth**: the percentage change in a firm's revenues between time *t* and *t-1*, where *t* represents the respective quarters within each of the three observation periods.
(2) **Stock returns:** the percentage change in a firm's stock price between time *t* and *t-1*, where prices were adjusted for corporate actions such as capital change, dividends, splits or mergers.

(3) **Profitability:** the absolute change in a firm's profitability between *t* and *t-1*, where profitability is calculated as the LTM operating income before depreciation as a percentage of total assets in time *t.*

Sales growth was chosen as a measure of firm performance as it provides a direct indicator of customer driven losses in sales and accounts for the effects of competitors' aggressive strategies to capture market share during periods of financial vulnerability. In addition, the analysis will explore how losses in sales lead to the decline in profits and firm value. Accordingly, changes in stock returns were used as a measure of change in firm value and the change in profitability is being considered to assess the impact on profits. Stock returns, however, are expected to be negatively correlated with leverage, as highly leveraged firms are likely to be more sensitive to economic downturns compared to those with lower leverage. Fortunately, operating income before depreciation does not exhibit this relationship, though it can be influenced by the firm's management. Specifically, accounting policies might be adjusted to temporarily boost operating income, helping to avoid technical default (Opler and Titman, 1994). To account for this, the LTM operating income was included in the calculation of profitability variables, capturing up to one year of quarterly operating income prior to the point of financial vulnerability and therefore off-setts any effects that may occur due to policy changes.

Furthermore, all three of the firm performance variables mentioned above are adjusted for industry performance by subtracting the 3-digit SIC industry averages of the respective firm performance measure, which allows to test within-industry effects.

The pooled OLS model employed will predict firm performance as a measure of the following independent variables:

(1) **Size**: the natural logarithm of total assets of firm *i* in time *t*.
(2) **Prior profitability**: the ratio of operating income before depreciation to the total assets by the 3-digit SIC industry average at time *t-1*.
(3) **Prior investment**: the change in net Property, Plant and Equipment (PP&E) between *t-1* and *t-2*.
(4) **Short-term investment**: the change in net working capital between *t* and *t-1*.

Due to the unavailability of quarterly data for investment variables such as capital expenditure and asset sales as well as inconsistencies in quarterly depreciation data, proxies were used to represent firm investment. Specifically, the lagged change in net PP&E and the change in net working capital were employed. Since capital expenditure consists of net PP&E plus

depreciation (CFI, 2024), the lagged change in net PP&E serves as a reliable proxy for long-term firm investment. To also account for short-term investment, the change in net working capital was included, as it reflects the short-term fund operations and binding of capital within a firm. To minimize the problem of reverse causality, profitability and investment were controlled by using lagged time periods since these variables can be determinants of sales growth and can therefore be influenced by it in the same period. This could occur if a company experiences higher sales growth and subsequently decides to reinvest more, which might also lead to these variables becoming correlated with leverage.

In addition to the prior introduced variables, three more independent dummy variables were added to the model:

(5) **High Leverage**: 1 if the firm's leverage is part of the top three leverage decile at time *t-1* and 0 otherwise. Leverage in this case is defined as total debt divided by total assets.
(6) **Distressed Industry**: 1 if the industry's average sales growth between *t* and *t-1* is negative, and the industry experiences two consecutive quarters of average negative stock returns; 0 otherwise.
(7) **High Leverage x Distressed Industry**: 1 if High Leverage and Distressed Industry is 1; 0 otherwise.

These three dummy variables were introduced to examine the linkage between leverage and performance during industry downturns, which is the central focus of this analysis. The use of dummy variables rather than continuous ones is motivated by the expectation that the relationship between leverage and performance is difficult to define and may also be nonlinear. To address potential endogeneity issues, leverage is measured with a one-quarter lag. This approach mitigates concerns that a firm's access to capital might be constrained during periods of financial distress. Moreover, using the current leverage ratio to assess distress could lead to a negative correlation between leverage and performance, as firms often increase borrowing when facing financial challenges (Opler and Titman, 1994).

To ensure industries are not mistakenly classified as financially distressed, two criteria are applied: consecutive negative stock returns and negative sales growth. The requirement for consecutive negative stock returns helps filter out downturns that financial market participants do not perceive either as long-term or significant. Similarly, the negative sales growth criterion is essential to exclude otherwise healthy industries that may experience negative stock returns due to overly optimistic prior expectations (Opler and Titman, 1994). Additionally, to account

for seasonality in industry sales and further reduce the risk of misclassification, industry sales data is adjusted using a multiplicative seasonal adjustment (Duke University, 2018). The high leverage x distressed industry dummy variable plays a crucial role in this model, since this explicitly explores the effect of high leverage on firm performance in times of distress.

Ultimately, the regressions for all three observation periods were run using panel data to capture both cross-sectional and time-series variations, allowing for a more comprehensive analysis. Consequently, the resulting regression is expressed as follows:

$$
\begin{aligned}
Firm\ performance_{it} &= \beta_0 + \beta_1\, Size_{it} + \beta_2\, prior\ profitability_{it} \\
&+ \beta_3\, prior\ investment_{it} \\
&+ \beta_4\, short - term\ investment_{\ it} \\
&+ \beta_5\, high\ leverage_{it} \\
&+ \beta_6\, distressed\ industry_{it} \\
&+ \beta_7\, high\ leverage\ x\ distressed\ industry_{it} + \epsilon_{it}
\end{aligned}
$$

3.3 Nonparametric Test

After testing the residuals from the above regression for normality, the results suggest that they do not follow a normal distribution, which raises concerns about the validity of the reported t-statistics for our estimates. Consequently, a nonparametric test of the hypothesis that leverage affects performance in depressed industries was run. A binomial test was conducted to assess whether the percentage of highly leveraged firms outperforming the industry median in distressed industries is statistically different from the percentage of highly leveraged firms outperforming the industry median in non-distressed industries. These tests were used for all three observation periods, indicating a significant difference between highly leveraged firms with profitability exceeding the sample median in distressed industries and those in non-distressed industries during the migration crisis and the COVID-19 pandemic. For the other two firm performance measures no significant differences could be found in both distressed and non-distressed industries across the different time spans.

4 Descriptive Statistics

Examining the data reveals that, compared to the COVID-19 pandemic and the Ukraine war period, the migration crisis had relatively fewer firms operating in poorly performing industries—only about 2.3%, compared to 9.5% and 11.3%, respectively. The exact numbers of firms operating in poorly performing industries can be seen in Table I distributed by period year and quarter. The migration crisis appears to have impacted German firms primarily during

2014 and the first quarter of 2015, after which no firm or industry met the criteria for being classified as distressed. This contrasts with the other two periods: during the COVID-19 pandemic, firms and industries faced distress in nearly every quarter of the observation period, except for two, aligning with the timeline of the outbreak and the associated lockdown measures. Similarly, the period surrounding Russia's invasion of Ukraine shows comparable patterns in the prevalence of distressed industries and the firms operating within them.

Table I
Distribution of Firms by Year and Period

The dataset includes 1,886 publicly traded firm quarters across all three periods. During the migration crisis, 696 firm-quarters were observed, with only 2.3% in distressed industries. The COVID-19 pandemic had 590 firm-quarters, with 9.5% in distressed industries, while the Ukraine war period included 600 firm-quarters, with 11.3% in poorly performing industries. Distressed industries were defined by negative average sales growth and negative quarter-on-quarter LTM stock returns.

Period	Quarter	No. Of Firms in Industries with Normal Performance	No. Of Firms in Industries with Poor Performance	No. Of Poorly Performing Industries
Migration Crisis	Q1 2014	57	1	1
	Q2 2014	55	3	1
	Q3 2014	52	6	2
	Q4 2014	55	3	1
	Q1 2015	55	3	1
	Q2 2015	58	0	0
	Q3 2015	58	0	0
	Q4 2015	58	0	0
	Q1 2016	58	0	0
	Q2 2016	58	0	0
	Q3 2016	58	0	0
	Q4 2016	58	0	0
COVID-19 Pandemic	Q1 2019	49	10	5
	Q2 2019	51	8	4
	Q3 2019	52	7	4
	Q4 2019	52	7	3
	Q1 2020	59	0	0
	Q2 2020	51	8	4
	Q3 2020	52	7	5
	Q4 2020	52	7	4
	Q1 2021	57	2	1
	Q2 2021	59	0	0
Ukraine War	Q3 2021	58	2	1
	Q4 2021	60	0	0
	Q1 2022	60	0	0
	Q2 2022	57	3	1
	Q3 2022	53	7	3
	Q4 2022	27	33	8
	Q1 2023	58	2	1
	Q2 2023	60	0	0
	Q3 2023	48	12	5
	Q4 2023	51	9	4

Furthermore, the criteria used to define distressed industries does not account for the severity of the distress. While the table indicates that more firms operate in distressed industries during the Ukraine War period compared to the COVID-19 sample, this does not necessarily imply that the sales declines or stock return reductions are larger. It is possible that the magnitude of distress, in terms of sales cuts and stock return declines, is still greater in the COVID-19 sample. To give further context to this, a look at the average sales growth and quarter-on-quarter LTM stock returns are given in Table II. The table shows that during the COVID-19 pandemic, 11 industries recorded negative average sales growth, accounting for approximately 55% of the industries in the sample. However, most of these declines were modest, typically ranging between 0% and -1%. A possible explanation for this is that many industries experienced significant recovery effects in late 2020 and 2021. These effects potentially influenced the overall averages for the COVID-19 sample and may also extended into the Ukraine War sample, that may have captured a substantial portion of these recovery dynamics, also affecting overall averages. In the Ukraine war sample, no industries show negative average sales growth; however, overall growth remains modest, typically ranging between 1% and 5% in most cases. Looking at some industry specifics, the Electric Services industry seems to be somewhat resilient to industry downturns, only during the COVID-19 pandemic sales growth decreases on average that was followed by a significant increase in the Ukraine war sample, however stock prices were on average positive in this industry throughout all three samples. The Transportation industry stood out as the only sector with a significant drop in sales growth, recording an average decline of -11.89%. This aligns with the travel restrictions imposed during the pandemic, which significantly affected airlines and travel agencies, leading to substantial distress due to limited revenue generation. Meanwhile, the Laboratory Apparatus Industry and the Surgical and Medical Instruments Industry demonstrate relatively low but consistent growth across the samples. These industries appear to be less affected by downturns, which seems reasonable, as their products are typically in constant demand regardless of price or industry fluctuations. In summary, the key patterns observed indicate that the COVID-19 pandemic had a broadly negative impact on sales growth and stock returns, with notable exceptions in the healthcare and utilities sectors. In contrast, the Ukraine War period appeared to have a less severe impact on sales growth and stock returns, with most industries showing positive sales growth and stock returns, potentially influenced by strong recovery effects in 2021.

Table II
Average Sales Growth and Stock Returns by Industry

The sample consists of 1,886 publicly traded firm-quarters in the three observation periods combined. During the COVID-19 pandemic, about 11 industries (55 percent) had negative average sales growth and 8 industries (40 percent) had negative average quarter-on-quarter Returns across all quarters of the observation period.

	Average Sales Growth			Average qoq Stock Return		
	Migration Crisis	COVID-19	Ukraine War	Migration Crisis	COVID-19	Ukraine War
Beverages	-0.03	-0.17	2.05	4.28	1.90	-0.90
Chemicals and Allied Products	-1.43	0.71	1.87	11.55	-1.53	0.33
Cogeneration Services		-0.72	5.15		5.55	6.87
Computer and Office Equipment	1.74	-0.74		5.23	-2.21	
Construction, Mining and Materials	1.12	0.68	3.09	3.13	-2.95	3.11
Electric Services	6.13	-0.42	11.06	7.88	5.41	2.74
Electrical Industrial Apparatus	-3.21			5.32		
Electronic components and Accessories	3.57	1.30	5.31	7.77	2.50	4.16
General Industrial Machinery and Equipment	1.67		2.77	3.46		4.83
Laboratory Apparatus and Furniture	2.03	3.21	3.22	4.27	3.89	2.22
Medical Chemicals & Botanical Products	2.05	2.48	1.80	1.09	-0.80	-6.12
Metalwork Machinery & Equipment	-1.70	-2.53	3.02	-0.08	-1.26	2.39
Motor Vehicles and Equipment	1.61	-0.09	2.64	3.09	2.13	3.22
Non-operating Establishments	-3.86	0.50	4.42	5.87	0.00	4.77
Plastic and Synthetical Materials	12.78	-0.01	3.38	7.68	-0.63	7.15
Radiotelephone Communications	2.08	2.27		9.41	-2.60	
Retail			4.90			0.88
Computer Programming and Data Processing	2.02	-0.14	1.19	2.17	3.90	2.08
Hospitals			1.23			3.56
Miscellaneous Business Services		-0.38	-1.24		1.58	2.72
Special Industry Machinery	0.53	-1.51	2.37	4.01	0.78	6.37
Surgical and Medical Instruments	0.72	0.84	2.95	4.27	-0.40	-2.56
Transportation		-11.89	21.32		5.59	17.41

Table III gives further information to that by looking at the descriptive statistics of variables. Examining Panel A, which presents data from the migration crisis, *Size* seems to be quite constant and not volatile at all, ranging from 5.06 in the first quartile to 7.75 in the third quartile and a mean of 6.69. However, more than 50% of the data observed has a negative lagged profitability, firms at the first quartile experience cuts of -5.6%, in contrast firms at the third quartile manage to capture positive values of 8.49% with the mean being -0.22%. Both investment ratios, being *Change in NPPE* and *Change in NWC* also seem to be relatively constant and not too volatile, ranging from -1.22% and -3.99% in the first quartile up to 3.99% and 7.75% in the third quartile. The same can be said for both Leverage measures, being quite close together even with the lag of one year, starting from 44.61% and 44.65% for the first quartile up to 70.11% and 70.50% for the third quartile. However, *Sales growth* and *Stock Returns* seemed to be slightly left skewed, showing negative means of -0.89% and -0.87% and data ranging from -6.56% and -9.65% in quartile one to 6.88% and 8.88% in the third quartile.

In comparison, Panel B, that shows the data of the COVID-19 pandemic, *Size* seems to be rather similar to Panel A, but *lagged Profitability* is much more negative. This variable has a mean of -21.88% with data ranging from -13.45% at quartile one to only about 1.29% at quartile three. While the *change in NPPE* also seems comparable to Panel A, the *change in NWC* is too more negative, with a mean of -29.47% and data ranging from -13.27% at quartile one up to 10.11% at quartile 3. Furthermore, Leverage ratios are also in similar data ranges as in Panel A, but *Sales Growth* and *Stock Return* look more volatile, having data ranging from -10.16% and -13.71% at quartile 1 to 11.04% and 14.59% at quartile three.

Finally, looking at Panel C *Size* again is in similar ranges compared to Panel A and B, but *lagged Profitability* seems only comparable to the COVID-19 data. The variable has a mean of -11.61% which is notably less negative compared to Panel B but also seems to have slightly left skewed data, -16.23% at quartile 1 and 1.03% at quartile 3. *Change in NPPE* again is quite similar to Panel B data, however, *Change in NWC* is on average significantly different to the periods before with a mean of 25.73%. Leverage ratios show a slightly decreasing trend, being roughly 3% less on average compared to the prior periods. Also, *Stock Returns* are significantly larger compared to Panel A and B, which also indicates potential recovery effects that happened after the COVID-19 pandemic during 2021.

Table III
Description of variables across samples

The sample consists of 1,886 publicly traded firm-quarters in the three observation periods combined. Assets are measured at book value; Ex ante Leverage is measured one year before the base year. Size, Change in NPPE and Change in NWC are measured according to their definition.

Variable	Mean	Quartile One	Median	Quartile Three
Panel A: Migration Crisis				
Size	6.69	5.06	6.07	7.75
Lagged Profitability (%)	3.18	-5.60	-0.22	8.49
Change in NPPE (%)	4.08	-1.22	0.47	3.99
Change in NWC (%)	0.34	-3.99	0.22	7.75
Ex ante debt/assets (%)	57.29	44.61	57.23	70.11
Base-year debt/assets (%)	57.38	44.65	58.67	70.50
Sales growth (%)	-0.89	-6.56	0.00	6.88
Stock return (%)	-0.87	-9.65	-0.11	8.88
Panel B: COVID-19				
Size	6.90	5.26	6.34	7.80
Lagged Profitability (%)	-21.88	-13.45	-1.58	1.29
Change in NPPE (%)	8.29	-1.90	0.28	5.59
Change in NWC (%)	-29.47	-13.27	-0.03	10.11
Ex ante debt/assets (%)	57.51	46.23	56.83	69.12
Base-year debt/assets (%)	58.43	46.63	57.75	70.12
Sales growth (%)	1.62	-10.16	1.46	11.04
Stock return (%)	1.44	-13.71	-0.09	14.59
Panel C: Ukraine War				
Size	6.59	5.03	6.04	7.54
Lagged Profitability (%)	-11.61	-16.23	-3.44	1.03
Change in NPPE (%)	3.19	-2.07	0.37	4.38
Change in NWC (%)	25.73	-12.08	1.24	12.09
Ex ante debt/assets (%)	55.84	43.37	55.04	67.15
Base-year debt/assets (%)	55.66	43.59	54.04	66.84
Sales growth (%)	0.60	-7.36	0.54	8.60
Stock return (%)	27.75	-12.27	-1.43	11.07

5 Results

This section presents the empirical findings from the pooled OLS regression analysis conducted, along with the results after checking for fixed effects and testing for robustness.

5.1 Leverage, Firm performance and Distressed Industries

The main question addressed in the employed pooled OLS regression is whether the effect of leverage on firm performance is greater when industries experience distress, measured by profitability, sales growth and stock returns. The results are reported in Table IV. Accordingly, of most interest are the coefficients of the *high leverage dummy* that shows varying results across the periods and firm performance measures. Industry-Adjusted Profitability is 0.6% higher during the migration crisis period and 1.9% higher during the Ukraine war period for firms in the top three leverage deciles. These results are also economically significant. However, for the COVID-19 sample, firms' industry-adjusted profitability is -1.8% lower on average compared to less leveraged firms, still this finding is not statistically significant. Notably, increasing *Size* had significant positive influence on industry-adjusted profitability in the COVID-19 and Ukraine War sample which is in line with findings of Hall and Weiss (1967). The results for the *high leverage x distressed industry dummy* may be counterintuitive but are statistically significant for both the Ukraine war period (at 1% significance level) and the COVID-19 sample (at 10% significance level). Specifically, findings indicate that industry-adjusted profitability is 29.4% higher for highly leveraged firms in distressed industries during the COVID-19 pandemic and 7.8% higher during the Ukraine war than there less leveraged counterparts. A potential explanation for this pattern could be the presence of "zombie firms," as identified by Álvarez et al. (2023). These distressed firms often receive financial support, such as new credit or loan refinancing, which can temporarily increase leverage. A notable proportion of these firms recover and exit distress within the following year, potentially driving improvements in profitability as they regain stability. Since high leverage is measured on an ex-ante basis, these observations align with the reported findings. This also aligns partially with the expectations of Opler and Titman (1994), who proposed that the interaction dummy would be positive for both industry-adjusted profitability and industry-adjusted stock returns if highly leveraged firms in distressed industries were able to downsize more effectively than their less leveraged peers. However, while the results confirm this expectation for industry-adjusted profitability during the COVID-19 and Ukraine war periods, the coefficients for the interaction variable remain negative across all periods for industry-adjusted stock returns, with none

Table IV

Pooled OLS Regressions Predicting Mean Industry-Adjusted Profitability, Sales Growth and Stock Returns in the three observation Periods.

The industry adjustments are carried out by subtracting the 3-digit SIC industry mean from the respective firm performance measures. Additionally, a binomial sign test was employed to measure the significance of the proportion of leveraged firms in distressed industries with above-median industry performance compared to the same proportion for leveraged firms in nondistressed industries.

	Industry-Adjusted Profitability			Industry-Adjusted Sales Growth			Industry-Adjusted Stock Returns		
	Migration Crisis	COVID-19	Ukraine War	Migration Crisis	COVID-19	Ukraine War	Migration Crisis	COVID-19	Ukraine War
Intercept	-0.012***	-0.226***	-0.044***	-0.015	-0.050	-0.007	0.053**	-0.008	0.597
	(0.002)	(0.060)	(0.001)	(0.028)	(0.074)	(0.037)	(0.025)	(0.028)	(0.863)
Size	-0.001	0.048***	0.003***	0.000	0.014	0.001	-0.010***	0.003	-0.082
	(0.000)	(0.008)	(0.001)	(0.004)	(0.010)	(0.005)	(0.004)	(0.004)	(0.119)
Prior profitability	-0.000	-0.000	0.002	0.000	-0.001	-0.014	0.001	-0.004**	0.163
	(0.000)	(0.004)	(0.002)	(0.002)	(0.005)	(0.013)	(0.002)	(0.002)	(0.311)
Prior investment	-0.003	0.026	0.003	0.019	-0.015	0.016	0.024	0.070***	-0.073
	(0.002)	(0.042)	(0.006)	(0.028)	(0.052)	(0.046)	(0.025)	(0.020)	(1.085)
Short-term investment	-0.003**	0.002	-0.000	0.020	0.001	-0.000	0.058***	-0.001	-0.002
	(0.001)	(0.004)	(0.000)	(0.015)	(0.005)	(0.003)	(0.013)	(0.002)	(0.064)
High leverage dummy	0.006***	-0.018	0.019***	0.013	-0.070	-0.036	0.031	-0.030	1.940***
	(0.002)	(0.056)	(0.004)	(0.026)	(0.068)	(0.032)	(0.023)	(0.026)	(0.749)
Distressed industry dummy	-0.002	0.035	0.000	0.022	-0.042	0.086**	-0.095	0.004	-0.006
	(0.007)	(0.082)	(0.005)	(0.091)	(0.100)	(0.038)	(0.080)	(0.038)	(0.905)
High leverage x distressed industry dummy	0.012	0.294*	0.078***	-0.039	-0.582***	0.105	-0.011	-0.051	-1.598
	(0.010)	(0.167)	(0.015)	(0.124)	(0.204)	(0.119)	(0.109)	(0.078)	(2.810)

Table IV - *Continued*

	Industry-Adjusted Profitability			Industry-Adjusted Sales Growth			Industry-Adjusted Stock Returns		
	Migration Crisis	COVID-19	Ukraine War	Migration Crisis	COVID-19	Ukraine War	Migration Crisis	COVID-19	Ukraine War
Adjusted R^2	0.0282	0.0473	0.1341	0.0039	0.0163	0.0047	0.0327	0.0179	0.0107
No. of observations	696	590	600	696	590	600	696	590	600
Proportion of leveraged firms above median industry performance in nondistressed industries (%)	67.27***	60.57**	81.19***	47.27	58.65*	42.57	51.81	50.00	51.49
Proportion of leveraged firms above median industry performance in distressed industries (%)	100.00***	81.25**	75.00	44.44	56.25	25.00	66.67	56.25	75.00

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

reaching statistical significance but indicating that financial distress is perceived as costly by financial market participants. The industry-adjusted sales growth regressions also generally support the idea that financial distress is costly. While most of the results lack statistical significance, the interaction and distressed industry dummy are economically significant at the 1% and 5% level. Firms operating in distressed industries during the Ukraine war experience on average 8.6% higher sales growth than firms operating in non-distressed industries. Firms that are highly leveraged and operate in distressed industries experience significant cuts in sales growth of -58.2% during the COVID-19 pandemic, indicating that leveraged firms lose a large market share during times of industry downturn to their more conservative financed peers. Additionally, *Size* has significant but mostly negative influence on industry-adjusted stock returns, however this observation is in line with the findings of Banz (1981) that show that smaller firms listed on the NYSE firms had significantly higher risk adjusted returns than their larger peers. Furthermore, the investment ratios indicate statistically significant results during the migration crisis and the COVID-19 period. Prior investment positively impacts industry-adjusted stock returns in most cases, boosting firms' stock returns by an average of 7% during the COVID-19 period (significant at the 1% level). However, no significant results were found in the other periods. In contrast, short-term investment, measured by the change in net working capital, produces mixed effects across the periods. During the migration crisis, it negatively impacted industry-adjusted profitability by -0.3% on average (significant at the 5% level), while it had a positive effect on industry-adjusted stock returns, increasing them by 5.8% on average (significant at the 1% level). This could be explained by the fact that financial market participants may view an increase in net working capital favorably, as it signals stronger liquidity and a firm's ability to meet short-term obligations due to higher current assets relative to current liabilities.

5.2 Time and Industry Fixed Effects

Given the variation observed within the data, meaning differences between industries but also quarters, fixed effects were incorporated into the model, results can be seen in Table V. Specifically, fixed effects for industry and time were added which allows testing for unobserved heterogeneity. Results show that including fixed effects substantially increased the adjusted R^2, this however could be caused by the assumption that all quarters and industries are allowed to be different, hence adding the fixed effect dummy variables to the model potentially inflates the adjusted R^2.

The introduction of fixed effects into the model does not substantially influence the coefficients in most cases. The direction of the coefficients remains consistent more often than not, and changes in their magnitudes are generally slight with some few deviations. Certain variables do exhibit notable differences after including time and industry fixed effects. For the profitability regressions, the coefficients for prior profitability, prior investment, and the distressed industry dummy change direction for the COVID-19 sample. Prior investment now has a negative effect of -3.6% (before 2.6%) on profitability, similarly firms operating in distressed industries now experience a negative effect of -3% (before 3.5%). Nevertheless, these changes remain statistically insignificant. In the Ukraine War sample, Size, high leverage and distressed industries also changed direction, with their effects on profitability not only becoming negative but also statistically insignificant. This indicates that these variables may be driven by unobserved heterogeneity that is now controlled for. The results of the sales growth regression seem to be quite robust, showing only changes of directions for both the COVID-19 and the Ukraine War sample for the high leverage dummy, which turned positive to 5% (before -7%) and 1.9% (before -3.6%) respectively. Furthermore, the distressed industry dummy does not remain statistically significant, again indicating potential unobserved heterogeneity during the Ukraine War sample. The inclusion of fixed effects significantly impacts the stock return regressions. For instance, both the intercept and the size coefficients lose their significance for the Migration Crisis. In contrast, in the COVID-19 sample, the intercept becomes significant, suggesting that once fixed effects are accounted for, there may be an underlying effect on stock returns that was previously suppressed. Adding to that, the inclusion of fixed effects results in almost all coefficients switching signs for the Ukraine War sample, with high leverage also becoming non-significant. The reason for that could be that relations between the explanatory variables and stock returns during this period are particularly sensitive to unobserved factors which makes results hard to interpret.

Generally, these findings indicate overall stability of most coefficients and therefore suggest robustness to the inclusion of fixed effects. However, due to the fact that some variables seem to be sensitive to unobserved factors while also facing lack of statistical significance in the overall model, observed relationships may not to be strong and consistent across the different samples.

5.3 Robustness

In addition to the robustness test already performed by checking for fixed industry- and time-effects, residual versus fitted value plots were also created to assess potential non-linearity. Figures 1 to 3, found in the appendix, provide the corresponding visual results, which align with the fixed effects check. The scatter plots reveal that most data points are concentrated in specific areas, suggesting non-linearity between the dependent and independent variables, as well as the potential presence of heteroscedasticity. While most scatter plots display concentrated clouds of data, the plot for the profitability regression shows a downward trend. Interestingly, the scatter plot for stock returns in the Ukraine war sample contains only three distinct clusters of highly concentrated data points. To further check for that issue a Breusch-Pagan test was applied. The results that are shown in Table VI show that in most cases the model exhibits a significant heteroscedasticity at a 1% percent significance level. Only the regression for industry-adjusted profitability of the Migration crisis sample and the regression for the industry-adjusted Stock returns of the COVID-19 sample do not show any sign of heteroscedasticity. As a result, robust standard errors are incorporated into the pooled OLS regression to adjust for the occurrence of heteroscedasticity. Additionally, the variables were tested for multicollinearity by examining the variance inflation (VIF) of each variable. The results indicate no issues with multicollinearity, as all VIF values are close to 1. Furthermore, testing for autocorrelation also shows no signs of distortion in this regard.

Results of these adjustments can be seen in Table VII in the appendix. It is observable that the overall significance of variables has decreased after adding fixed effects and robust standard errors into the model. However, these estimates are expected to be more accurate when predicting the coefficients and effects of the independent variables on the dependent variables and therefore provide a more accurate reflection of the relationship between the variables. In general, the magnitude and the direction of the estimates didn't change a lot, however the high leverage x distressed industry dummy turns insignificant for both the profitability regression and the sales growth regression, suggesting that the relationship observed before was not accurate. Furthermore, the Size variable now is significant in the profitability regression for both the Migration crisis and the COVID-19 period.

Table V

Pooled OLS Regressions Predicting Mean Industry-Adjusted Profitability, Sales Growth and Stock Returns in the three observation Periods and introducing fixed effects

The industry adjustments are carried out by subtracting the 3-digit SIC industry mean from the respective firm performance measures. Additionally, a binomial sign test was employed to measure the significance of the proportion of leveraged firms in distressed industries with above-median industry performance compared to the same proportion for leveraged firms in nondistressed industries.

	Industry-Adjusted Profitability			Industry-Adjusted Sales Growth			Industry-Adjusted Stock Returns		
	Migration Crisis	COVID-19	Ukraine War	Migration Crisis	COVID-19	Ukraine War	Migration Crisis	COVID-19	Ukraine War
Intercept	-0.013***	-0.189	-0.028***	-0.089	-0.081	-0.100	0.035	-0.264***	-0.404
	(0.007)	(0.325)	(0.009)	(0.068)	(0.197)	(0.072)	(0.059)	(0.061)	(1.688)
Size	-0.001	0.054**	-0.001	0.007	0.019	0.002	-0.007	0.002	0.014
	(0.001)	(0.027)	(0.001)	(0.007)	(0.017)	(0.009)	(0.006)	(0.005)	(0.217)
Prior profitability	-0.000	0.009	0.001	-0.001	-0.008	-0.016	0.001	-0.004*	-0.028
	(0.000)	(0.009)	(0.002)	(0.002)	(0.007)	(0.015)	(0.002)	(0.003)	(0.358)
Prior investment	-0.002	-0.036	0.000	0.013	-0.035	0.003	0.013	0.040**	0.214
	(0.002)	(0.038)	(0.005)	(0.028)	(0.053)	(0.047)	(0.025)	(0.016)	(1.093)
Short-term investment	-0.002*	0.001	-0.000	0.016	0.001	-0.001	0.055***	0.001	-0.022
	(0.001)	(0.004)	(0.000)	(0.015)	(0.005)	(0.003)	(0.013)	(0.002)	(0.063)
High leverage dummy	0.000	-0.048	-0.007	0.005	0.050	0.019	0.003	-0.020	0.173
	(0.003)	(0.076)	(0.004)	(0.032)	(0.079)	(0.041)	(0.028)	(0.031)	(0.953)
Distressed industry dummy	-0.004	-0.030	-0.007	-0.022	-0.001	0.069	-0.124	0.029	0.312
	(0.007)	(0.076)	(0.005)	(0.098)	(0.109)	(0.046)	(0.086)	(0.063)	(1.075)
High leverage x distressed industry dummy	0.011	0.208	0.074***	0.009	-0.635***	0.044	-0.017	-0.067	0.200
	(0.009)	(0.147)	(0.013)	(0.124)	(0.204)	(0.120)	(0.108)	(0.080)	(2.805)

Table V - *Continued*

	Industry-Adjusted Profitability			Industry-Adjusted Sales Growth			Industry-Adjusted Stock Returns		
	Migration Crisis	COVID-19	Ukraine War	Migration Crisis	COVID-19	Ukraine War	Migration Crisis	COVID-19	Ukraine War
Adjusted R^2	0.2936	0.2163	0.3584	0.0683	0.1394	0.0810	0.1248	0.4322	0.0968
No. of observations	696	590	600	696	590	600	696	590	600
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** Significant at the 1 percent level.
** Significant at the 5 percent level.
* Significant at the 10 percent level.

Table VI
Test for heteroskedasticity

This table reports the results of the Breusch-Pagan test done for heteroskedasticity for the firm performance measures predicted with the pooled OLS regression defined in Section 3.

	Industry-Adjusted Profitability			Industry-Adjusted Sales Growth			Industry-Adjusted Stock Returns		
Statistic	Migration Crisis	COVID-19	Ukraine War	Migration Crisis	COVID-19	Ukraine War	Migration Crisis	COVID-19	Ukraine War
Chi^2	2.98	634.09	1280.97	12.3	2835.03	231.72	11.66	2.05	2490.02
P-Value	0.0843	0.0000	0.0000	0.0005	0.0000	0.0000	0.0006	0.1526	0.0000

6 Summary and Conclusions

Following the presentation of the pooled OLS regression results for all three observation periods, this section will focus on discussing the key findings, addressing potential limitations that may have affected the results, and suggesting directions for future research in this area.

6.1 Key Findings

The study was conducted to explore the relationship between financial condition and firm performance in industry downturns. For that reason, the firm performance of publicly traded German firms was analyzed during the recent downturn that originated by the outbreak of the Invasion of the Ukraine by Russia but also for the last two downturns that happened due to the outbreak of the COVID-19 virus and the migration crisis.

During the Migration crisis, high leverage had a small but positive effect on profitability, sales growth and stock returns, still none of these effects were found to be significant. During the same period firms operating in distressed industries experienced negative effects on all three firm performance measures, again without statistical significance. The interaction dummy between the two affected profitability and sales growth positively and stock returns negatively, again remaining insignificant.

For the COVID-19 sample, high leverage had negative effects on profitability and stock returns, and positive effects on sales growth, none of them being significant. Firms operating in distressed industries experienced negative effects on profitability and sales growth and positive effects on stock returns, also being insignificant. The interaction dummy coefficients show significant (at the 1% level) and substantial declines in sales growth and smaller negative effects on stock returns, effects for profitability were rather big and positive but insignificant.

Lastly, for the Ukraine War period high leverage had positive effects on sales growth and stock returns but negative effects on profitability. The exact same directions can be seen for firms operating in distressed industries during this period, however, none of these observations are significant. The interaction dummy on the other hand seemed to have positively influenced firm performance in this period, even showing a significant effect on profitability (at the 1% level).

Ultimately, the findings indicate that this analysis did not observe a significant relationship between financial condition and firm performance in most cases. However, it was found that highly leveraged firms operating in distressed industries experienced substantial and significant declines in sales growth, aligning with earlier research such as Opler and Titman (1994). Additionally, the results suggest a tendency for profitability to be positively influenced by high

leverage and distressed industry conditions, while the same variable appears to have a negative impact on stock returns.

6.2 Limitations

The analysis conducted faced several limitations, primarily related to the methodological design. Due to the relatively short time frames of industry downturns, quarterly data was used to examine the relationship between financial condition and firm performance. However, this approach introduced significant challenges in data collection. For instance, some variables used in the original study were reported annually rather than quarterly, which required modifications to the industry-adjusted investment ratios, making them proxies rather than direct measures based on accounting data. This also includes research and development data, capital expenditures, asset sales and quarterly depreciation. Additionally, the criteria for selecting industries led to a notable limitation in the sample size, as many publicly listed firms operate in industries with fewer than four publicly traded companies. Moreover, a considerable number of firms were excluded from the analysis due to missing data in certain quarters, with only firms that had complete data across all variables and quarters being included in the sample. Additionally, assuming that ex ante leverage is exogenous may have influenced interpretability negatively, because for this assumption to hold identical firms need to choose different leverage ratios. The underlying reason for different leverage ratios therefore would not be directly modeled in this analysis. Furthermore, industries and firms that are healthy could be defined as distressed and vice versa, since this methodology only takes sales growth and stock returns into account to define distress while neglecting other constituents of the Altman Z-score (1968) such as liquidity or earnings. This way the sample could include a substantial number of firms or industries that are not really distressed and exclude substantial numbers that are distressed. Lastly, this model assumes that the capital structure decision is endogenous, that way results potentially underestimate the negative impact of leverage on performance if firms with the highest cost of financial distress are also the least likely to be highly leveraged.

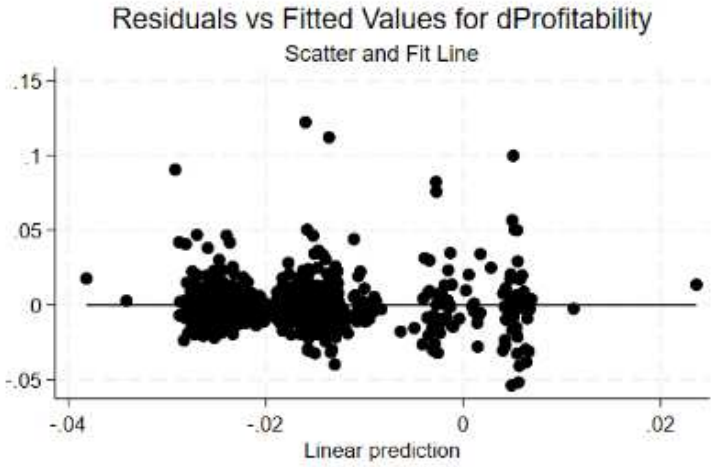
6.3 Conclusion

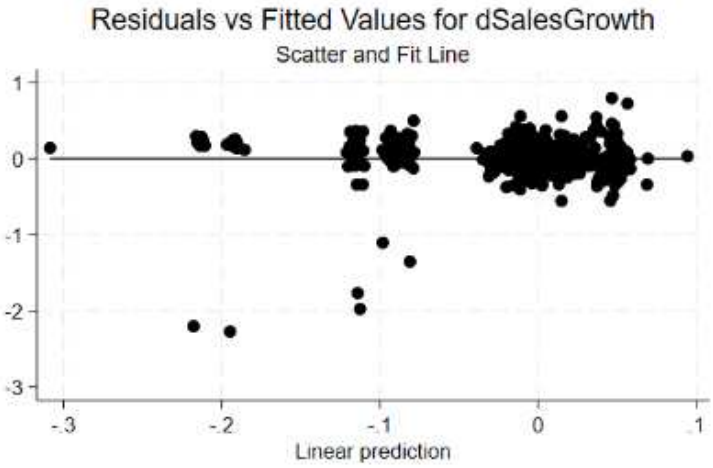
The studies aim was to find out if highly leveraged publicly traded German firms are more likely to experience performance losses in comparison to their less leveraged counterparts during the Ukraine war period. Although this study did not find statistically significant results to answer the research question, certain trends can still be seen. Contrary to the findings of Opler and Titman (1994), high leverage did not have a negative impact on firm performance during industry downturns. Instead, the results suggest that high leverage had a positive effect

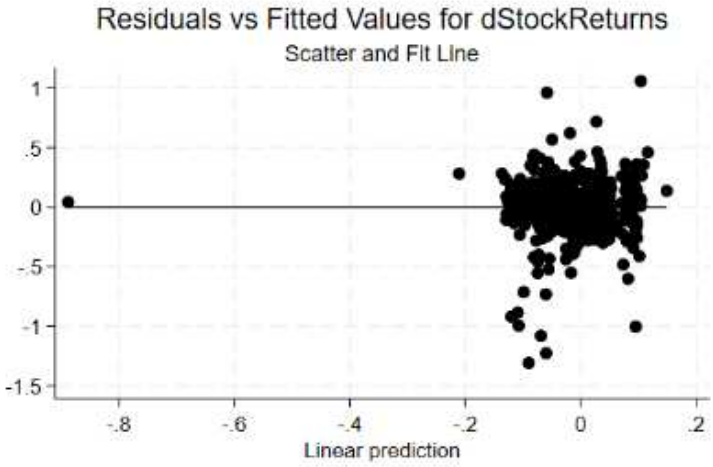
on firm performance in these periods. This could be attributed to a significant number of firms operating in distressed industries that successfully downsize in response to downturns, leading to improvements in performance as they regain stability, as observed by Álvarez et al. (2023). Adding to that, this study was also able to find a significant positive impact of highly leveraged firms that operate in distressed industries on profitability, suggesting again potential effective downsizing of firms. However, since there is no statistically significant answer to the research question in most periods and variables, additional research could further explore how financial condition affects firm performance during industry downturns. For that, research could alter the research design and thereby improve the explanatory power of the model. Switching to yearly data and extending the observation period would increase sample size and allow to introduce variables as used by Opler and Titman (1994), which would also make results more comparable. Furthermore, research could potentially switch from examining distressed industries to distressed firms, as a result empirical tests should become more powerful as relationships between choice of capital structure and financial condition should become more evident. Additionally, this would allow to introduce more firm specific distress measures and therefore minimize the problem of falsely classifying firms or industries.

7 Appendix

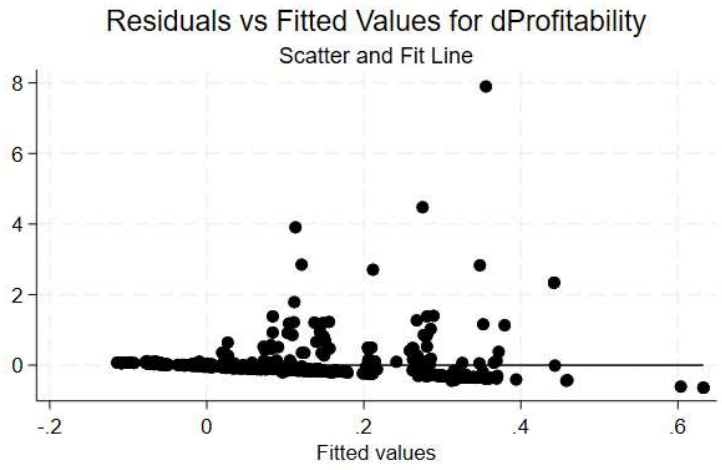
7.1 Scatter Plot for residuals of the Migration Crisis

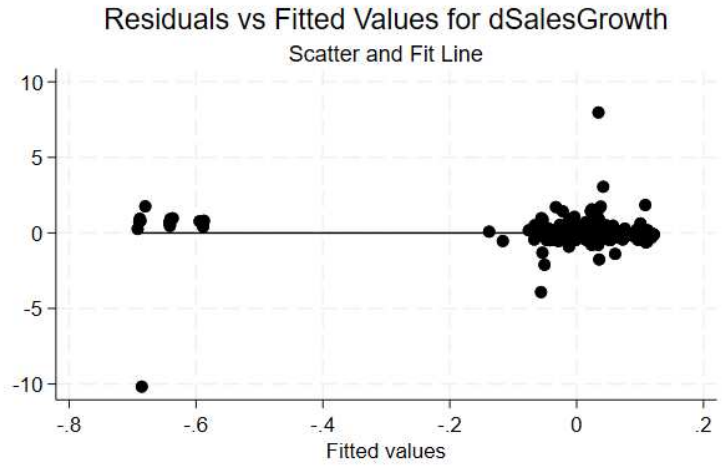


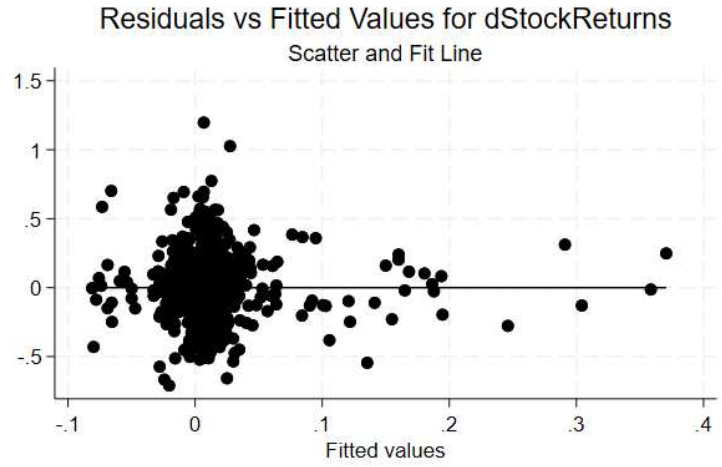




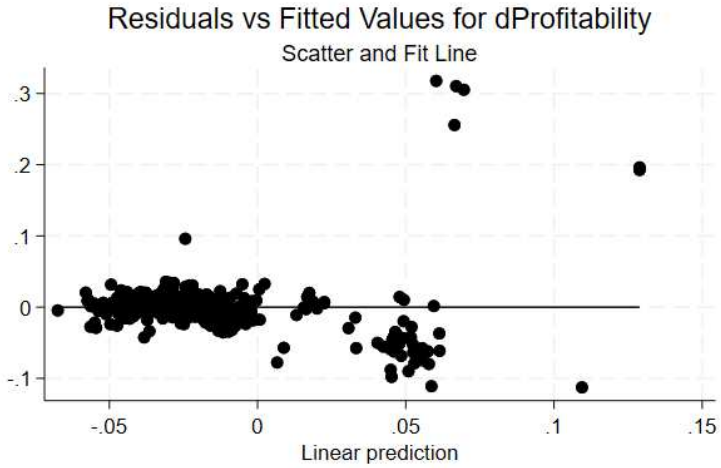
7.2 Scatter Plot for the residuals of the COVID-19 pandemic

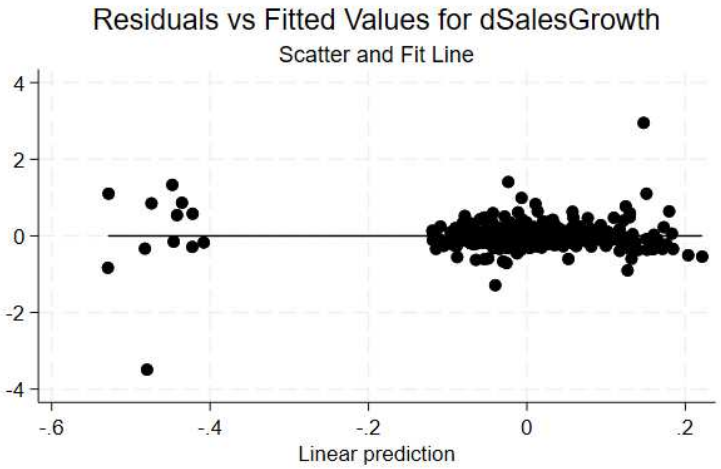






7.3 Scatterplot for the residuals of the Ukraine War





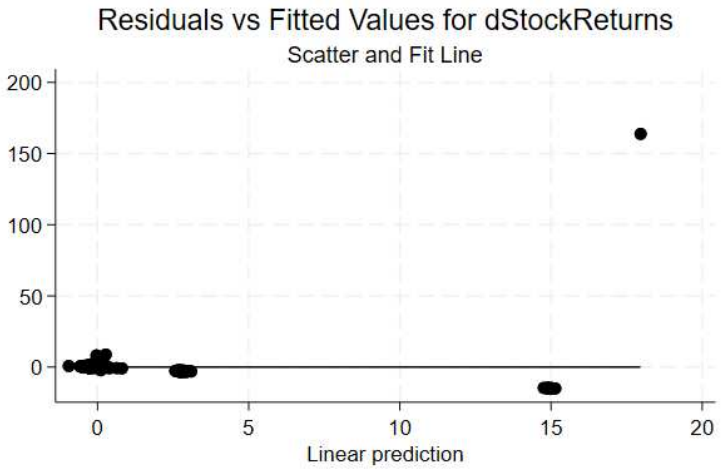


Table VII

Pooled OLS Regressions Predicting Mean Industry-Adjusted Profitability, Sales Growth and Stock Returns in the three observation Periods with fixed effects and robust standard errors.

The industry adjustments are carried out by subtracting the 3-digit SIC industry mean from the respective firm performance measures. Additionally, a binomial sign test was employed to measure the significance of the proportion of leveraged firms in distressed industries with above-median industry performance compared to the same proportion for leveraged firms in nondistressed industries.

	Industry-Adjusted Profitability			Industry-Adjusted Sales Growth			Industry-Adjusted Stock Returns		
	Migration Crisis	COVID-19	Ukraine War	Migration Crisis	COVID-19	Ukraine War	Migration Crisis	COVID-19	Ukraine War
Intercept	-0.013***	-0.154**	-0.028***	-0.089	-0.081	-0.100**	0.035	-0.264***	-0.404
	(0.004)	(0.073)	(0-007)	(0.065)	(0.081)	(0.050)	(0.045)	(0.065)	(0.458)
Size	-0.001**	0.043***	-0.001	0.007	0.019	0.002	-0.007	0.002	0.014
	(0.000)	(0.014)	(0.002)	(0.006)	(0.014)	(0.009)	(0.005)	(0.005)	(0.034)
Prior profitability	-0.000	0.020	0.001	-0.001	-0.008	-0.016	0.001	-0.004*	-0.028
	(0.000)	(0.015)	(0.000)	(0.001)	(0.006)	(0.016)	(0.001)	(0.002)	(0.061)
Prior investment	-0.002	-0.048	-0.000	0.013	-0.035	0.003	0.015	0.040**	0.214
	(0.001)	(0.031)	(0.002)	(0.010)	(0.030)	(0.021)	(0.015)	(0.020)	(0.295)
Short-term investment	-0.003***	0.003	-0.000	0.016	0.001	-0.001	0.055***	0.001	-0.022
	(0.001)	(0.002)	(0.000)	(0.010)	(0.003)	(0.001)	(0.005)	(0.001)	(0.023)
High leverage dummy	0.002	-0.009	-0.007	0.005	0.050	0.019	0.003	-0.020	0.173
	(0.002)	(0.061)	(0.008)	(0.017)	(0.067)	(0.060)	(0.029)	(0.024)	(0.203)
Distressed industry dummy	-0.004	-0.043	-0.007	-0.021	-0.001	0.069**	-0.124	0.029	0.312
	(0.003)	(0.097)	(0.005)	(0.034)	(0.079)	(0.033)	(0.197)	(0.028)	(0.350)
High leverage x distressed industry dummy	0.011*	0.237	0.074	0.009	-0.635	0.040	-0.017	-0.067	0.200

	(0.006)	(0.244)	(0.049)	(0.058)	(0.720)	(0.181)	(0.302)	(0.054)	(0.373)

Table VII - *Continued*

	Industry-Adjusted Profitability			Industry-Adjusted Sales Growth			Industry-Adjusted Stock Returns		
	Migration Crisis	COVID-19	Ukraine War	Migration Crisis	COVID-19	Ukraine War	Migration Crisis	COVID-19	Ukraine War
Adjusted R^2	0.295	0.221	0.3584	0.068	0.1394	0.0810	0.125	0.4322	0.0968
No. of observations	696	590	600	696	590	600	696	590	600
Proportion of leveraged firms above median industry performance in nondistressed industries (%)	67.27***	60.57**	81.19***	47.27	58.65*	42.57	51.81	50.00	51.49
Proportion of leveraged firms above median industry performance in distressed industries (%)	100.00***	81.25**	75.00	44.44	56.25	25.00	66.67	56.25	75.00
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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