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Quantitative easing and the use of bonds in the debt structure of mergers and acquisitions in the European Union

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Generative AI tools (e.g., ChatGPT) were used to assist in coding, data analysis, and/or refining the language of this thesis. Appendix B of this thesis provides a detailed account of the use of Generative AI tools during the development of this thesis. By submitting this thesis, I declare that I am fully responsible for the accuracy and completeness of its content.

abstract

Does quantitative easing impact the ratio of bonds in the capital structure of mergers and acquisitions? This thesis constructs a proprietary dataset using European mergers and acquisitions data, acquirer bond data and a proxy for monetary policy to show that acquirers use a larger ratio of bonds in the capital structure of M&A-transactions under quantitative easing conditions. A one percent decrease in the policy rate is equal to a 20,1% increase in the ratio of bonds in the debt structure of acquiring firms. This relationship helps firm managers in capital structure decisions and policymakers in understanding the effects of monetary policy in practice.

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1 Introduction

1.1 Introduction to the research field

Economic circumstances play a key role in the success of mergers and acquisitions, as they have a large influence on the reallocation of capital and asset prices. Monetary policy plays an important role in macroeconomic outcomes and has a big impact on future prices and expected returns (Fischer & Horn, 2021; Obonyo, 2022). Besides, monetary policy influences resource allocation decisions, impacts the availability of capital and bond issuance, encourages corporate risk taking, and could impose financing challenges for investors (Beaudry et al., 2014; Grosse-Rueschkamp et al., 2019; Jiménez et al., 2014). Axelson et al. (2007) found that economy wide credit conditions are a determining factor in leverage in mergers and acquisitions. However, relatively little is known about the relationship between monetary policy and the debt structure of merger and acquisition transactions.

During economic crises, conventional monetary policy is often used to combat these crises. However, when central bank interest rates were near zero and the economic landscape was not responding to the conventional monetary policy measures, central banks faced a major issue. In some cases, asset purchase programs were employed by central banks to stimulate economic growth and combat low inflation when conventional monetary policy was no longer able to do so. In recent history, central banks in the United States, Japan and Europe resorted to quantitative easing, the purchase of assets on the secondary market by central banks, with varying degrees of success.

Quantitative easing affects financial markets through multiple channels. Asset purchases under the Quantitative easing programs drive up demand and consequently, prices for these securities. These purchases intend to motivate banks to give out more loans to issue more asset-backed securities and bonds, lowering interest rates, driving up asset prices and lowering yields, impacting the cost of debt. Besides, if these additional funds are invested outside the EU-area, the increased demand for foreign currency depreciates the value of the euro, increasing inflation and making imports from the EU more attractive for foreign countries.

Due to the large impact of quantitative easing on the general economy, corporate boards should not neglect monetary policy in investment decisions and capital allocation of their firm, especially not investment decisions as significant as a merger or acquisition (Fischer & Horn, 2021). Mergers and acquisitions can be complex, demanding and resource intensive. The success of a merger or acquisition is dependent on the synergies following from the merger (Fischer & Horn, 2021; Obonyo, 2022). The extent and success of synergies is largely dependent on the macroeconomic landscape before, during and after the merger or acquisition is completed. It is important to know how specific monetary policy measures such as quantitative easing affect the capital structure of mergers and acquisitions, to optimize investment decisions and capital allocation, as monetary policy has a significant impact on the macroeconomic landscape. Corporate finance literature has established for which purposes firms shift from bank loans to bond issuance. Monetary policy literature has established a relationship between quantitative easing policy and the issuance of corporate bonds. However, to the extent of the knowledge of the author, no study has tried to establish a relationship between quantitative easing and the ratio of bonds in the debt structure of mergers and acquisitions. This thesis aims to fill this gap by relating increased corporate bond issuance and lower cost of debt due to quantitative easing to bonds issued to finance mergers and acquisitions, by answering the following research question:

How does quantitative easing affect the use of corporate bonds in the debt structure of acquiring firms in merger and acquisition transactions in the European union?

This thesis contributes to two strands of research. First of all, this thesis contributes to the body of literature on the effects of monetary policy on mergers and acquisitions. First, it contributes to the rather young and lively strand of literature on the effects of Quantitative easing measures on the primary bond market and bond yield spreads by examining the effects of Asset Purchase Programs (APPs) on bond issuance with regards to mergers and acquisitions. Secondly, this thesis contributes to the literature of capital structures in mergers and acquisitions by investigating the role of monetary policy in the form of APPs on the debt structure of M&A-transactions. More specifically, this paper combines these two bodies of research to investigate how quantitative easing affects the use of bonds in order to finance mergers and acquisitions.

On top of that, this thesis helps policymakers and central banks in understanding the consequences of their policy in practice. Besides, this thesis aids financial and legal professionals in consultancy firms, law firms and investments banks in giving accurate advice and counsel to their clients. Furthermore, this thesis aids firm managers themselves in understanding the impact of unconventional monetary policy on capital structure decisions and helping them make better financial decisions with regards to mergers and acquisitions.

The structure of this thesis is as follows. Section 2 provides an overview of existing literature. The literature review is divided into two parts, the first part is about capital structures and drivers of leverage in mergers and acquisitions. The second part of the literature review captures the existing literature of the effect of the asset purchase programmes on corporate debt and bonds. From the existing literature, the hypotheses and central research question are derived. In section 3, the methodology is explained. This section captures the empirical strategy and definition of variables and concepts. In section 4, the data collection strategy, preparation, descriptive statistics and OLS-assumptions are discussed. In section 5, results are presented, discussed against their theoretical background and tested for their robustness. Section 6 entails the conclusion and discussion sections.

2 Literature review

2.1 Drivers of leverage in mergers and acquisitions

Understanding capital structure and drivers of debt and equity levels within firms is essential to understand how monetary policy impacts financial decisions of firms, due to the fact that effective financial management and a fitting capital structure play a key role in the operational performance of a firm (Chen & Chen, 2011). Ineffective financial management can lead to financial distress or even bankruptcy. In order to optimize operational performance and prevent financial distress or bankruptcy, it is essential to get an understanding of how firms manage their funds effectively. Two main streams of capital structure follow from literature.

The first theory is the static trade-off theory of capital structure (Modigliani & Miller, 1958). The static trade-off theory of capital structure states that firms choose between debt and equity financing by balancing the benefits and costs of both debt and equity financing. Firms will choose for equity or debt financing based on the benefits and costs equity financing provides to the firm. The second main theory on firm capital structure is the pecking order theory. The pecking order theory states that firms will choose financing based on preference, with internal financing as the most attractive, followed by debt financing and equity financing (Shyam-Sunder & C. Myers, 1999).

Generally, the aforementioned theories on capital structures relate to the general capital structure and debt and equity levels within firms. It is currently unknown if these general theories apply to specific cases such as mergers and acquisitions (De Maeseneire & Brinkhuis, 2012). Due to the complex nature, extensive financial constraints, and different firm capital requirements with regards to mergers and acquisitions, these more general theories on capital structure and debt and equity levels might not hold for these kinds of investment projects.

It is vital to get a grasp of capital structures and drivers of debt levels with regards to mergers and acquisitions in particular, as debt financing has a large impact on financial flexibility of the acquiring firm (De Maeseneire & Brinkhuis, 2012). Financial flexibility dictates the access of the acquiring firm to outside financing when unexpected shocks or investment opportunities arise (Gamba & Triantis, 2008). Literature on leverage levels in leveraged buyouts suggests that financial flexibility is an important driver of firm capital structure decisions (Myers & Majluf, 1984). Not all M&A deals are created equal, so it is to be expected that the type of deal impacts the debt levels of the acquiring firm. Axelson et al. (2007) found that there was no significant difference in debt level for primary buyouts, the first-time stakes in firms are bought by private equity companies and secondary buyouts, when stakes are bought in firms that are already bought by private equity firms. Another factor driving leverage in buyouts is the nature of the relationship between banks and the acquirer (De Maeseneire & Brinkhuis, 2012). Concluding, financial flexibility is an important driver of debt levels in mergers and acquisitions.

Another driver of debt levels of the acquiring firm in mergers and acquisitions is firm size. As larger firms have lower expected pre-bankruptcy costs and lower informational and transactional costs when issuing debt (Ang et al. 1982; Warner, 1977). lower pre-bankruptcy costs have a positive relationship with debt levels in financing. This follows from the static trade-off theory. Acquirer firm size is thus expected to impact debt levels in M&A transactions.

Firms are more likely to issue debt at times when the cost of debt is low, which affects merger and acquisition transactions as well. The market timing theory states that the levels of equity and debt issued by firms is determined by the cost of debt and equity at the time of issuance (Baker & Wurgler, 2002).The cost of debt is described as the debt market liquidity, which in literature is proxied by interest rates and credit spread in the capital market (De Maeseneire & Brinkhuis, 2012). Credit spreads follow from market liquidity and act as a compensation for credit risk (Longstaff et al., 2005; Remolona et al., 2003).

With regards to the role of monetary policy on firm debt levels for mergers and acquisitions, a rise in the federal funds rate, the U.S. interbank interest rate, is associated with a rising cost of debt as well as indebtedness of acquiring firms (Adra et al., 2020). According to the authors, restrictive monetary policy increases the cost of financing, reducing the viability of firm projects like mergers and acquisitions, which is in line with the market timing theory. As mergers and acquisitions require extensive funding, future business operations become increasingly reliant on outside funding increasing firm debt levels, negatively impacting investor sentiment. On the contrary of the findings of Adra et al. (2020), expansionary monetary policy is associated with a lower cost of debt and indebtedness of acquirers.

The relationship between drivers of leverage in mergers and acquisitions has been studied thoroughly. The pecking order theory states that firms prefer using their own resources for financing over debt financing, but the complicated nature of mergers and acquisitions could mean that this theory does not hold in practice. Empirical studies show that firm size, firm flexibility, and cost of debt impact the amount of leverage in M&A transactions. In turn, expansionary monetary policy is expected to be associated with a lower cost of debt and increased viability of mergers and acquisitions. This theoretical framework suggests that expansionary monetary policy lowers the cost of debt for acquiring firms, increasing the likelihood that firms issue more debt to finance their project. However, there is a gap in the literature with regards to specific drivers of the cost of debt and their influence on leverage levels in merger and acquisition transactions.

2.2 Asset purchase programs, the cost of debt and corporate bond issuance

The ECB Quantitative easing programs are programs with which the ECB, together with national central banks, purchased assets on the secondary capital markets. Around 2014, the ECB implemented Quantitative easing, after facing some resistance from Germany. In 2015, the ECB launched the Asset Purchase Programme, or APP for short. The APP involved the purchase of securities and bonds valued at sixty billion euros per month from March 2015 up until March 2016, which increased to eighty billion euros per month from April 2016 until March 2017. After March 2017, the ECB started decreasing the value of the assets purchased under the APP, only to restart the APP for the COVID-19 crisis in 2019 up until June 2022. The APP consisted of multiple smaller purchase programmes. The APP consisted of the corporate sector purchase programme (CSPP), which entailed purchasing corporate sector bonds, the public sector purchase programme (PSPP), which entailed the purchase of inflation-linked and nominal central government bonds and bonds issued by local governments and recognized agencies, the asset-backed securities programme (ABSPP) and the third covered bonds purchase programme (CBPP3).

These asset purchase programs impact the European and global economy through three main channels. These channels are the signalling channel, the portfolio rebalancing channel, and the direct pass-through channel The effect of quantitative easing programs on the cost of debt and debt market liquidity will be discussed for each of these channels to study the effects of each of these channels to get a thorough understanding of the ways quantitative easing impacts leverage in mergers and acquisitions. But in order to get an understanding of how an unconventional monetary policy measure such as quantitative easing affects mergers and acquisitions, it is important to get a clear view of how general monetary policy affects mergers and acquisitions. Monetary tightening is associated with a higher cost of financing (Bernanke & Blinder, 1990). It is expected that the announcement of tightening monetary policy is going to increase the cost of debt. Besides, contractionary policy is associated with dampened M&A-activity both deal volume and total deal value, but the transactions that proceed, are perceived to be of higher quality (Fischer & Horn, 2021). Besides, target firms receive lower acquisition premiums and cumulative abnormal returns under tightening monetary policy (Obonyo, 2022).

The signalling channel signals that the central bank will keep interest rates low for an extended period, reducing volatility and uncertainty in the market, as well as interest rates on loans (ECB 2016). According to Krishnamurty & Vissing-Jorgensen (2011), the signaling channel of the asset purchase programs impacts the real economy. Through the asset purchase programs, the ECB purchases bonds with a long time to maturity. These purchases signal that the ECB will keep interest rates low for the near future, as rising interest rates will significantly lower the price of these bonds. This in turn influences bond spreads and the cost of debt.

The Asset purchase programs also impact the debt markets through the portfolio rebalance channel. As central banks purchase long maturity bonds from banks and other firms, these assets shift from private bank and firm balance sheets to central bank balance sheets, providing large amounts of cash into the economy. The vast amount of available cash, together with the fact that the sold assets are not perfectly substitutable, will have private firms looking at other assets that central banks are not eligible for purchase under the asset purchase program, to hedge risks and create returns. This rebalancing of private portfolios increases demand for bonds and lowers yields for financial products not eligible under the asset purchase programs.

The ECB's covered bond purchase programs (CBPP1 and CBPP3) reduced corporate bond spreads, while CBPP2, ABSPP, and PSPP showed no impact on bond spreads. The corporate sector purchase programme significantly reduces corporate bond spreads for bonds eligible under the CSPP as well as bonds that are not eligible under the CSPP. Besides the CSPP, the purchases of covered bonds under CBPP1 and CBPP3 influenced corporate bond spreads through the portfolio rebalancing channel. The CSPP increased the chance that firms substitute syndicated bank loans with long term bonds. However, this result does not hold for all firms in the sample. Firms that already use bond and bank debt in their financing are not affected by the CSPP (Kanda et al., 2025; Zaghini, 2019).

The study by Zaghini (2019) found a decrease of approximately 30 bps in yield spread for bonds issued on the primary market. The yield spreads for bonds eligible under the CSPP were 70 basis points lower than bonds not eligible under the asset purchase programs. After some time, this difference in spread decreased, showing that the CSPP also decreased bond spreads for non-eligible bonds through the portfolio rebalancing channel (Zaghini, 2019). Vayanos & Vila (2021) also find lower yield spreads for both eligible and ineligible bonds under the CSPP, both during the announcement period and the implementation period, in line with the signaling and portfolio rebalancing channel. Besides, they found that the CSPP impacted debt financing choices, as firms were more likely to opt for market debt instead of bank debt. However, monetary policy does not impact each sector and country in the same manner (Carlino & DeFina, 1999; Jansen et al., 2013). In order to optimize investment decisions and capital allocation for mergers and acquisition, it is important to know how monetary policy affects the merger and acquisition market for different sectors and countries.

The effects of Quantitative easing on the European economy have been studied extensively in recent years, showing lower effective interest rates, increased private and public lending by banks and lower bond yields for both eligible and non-eligible bonds. Research has shown that quantitative easing has led to lower cost of debt, as well as a shift from bank loans to bond issuance by firms requiring debt financing. The aforementioned literature results in the model in figure 1.

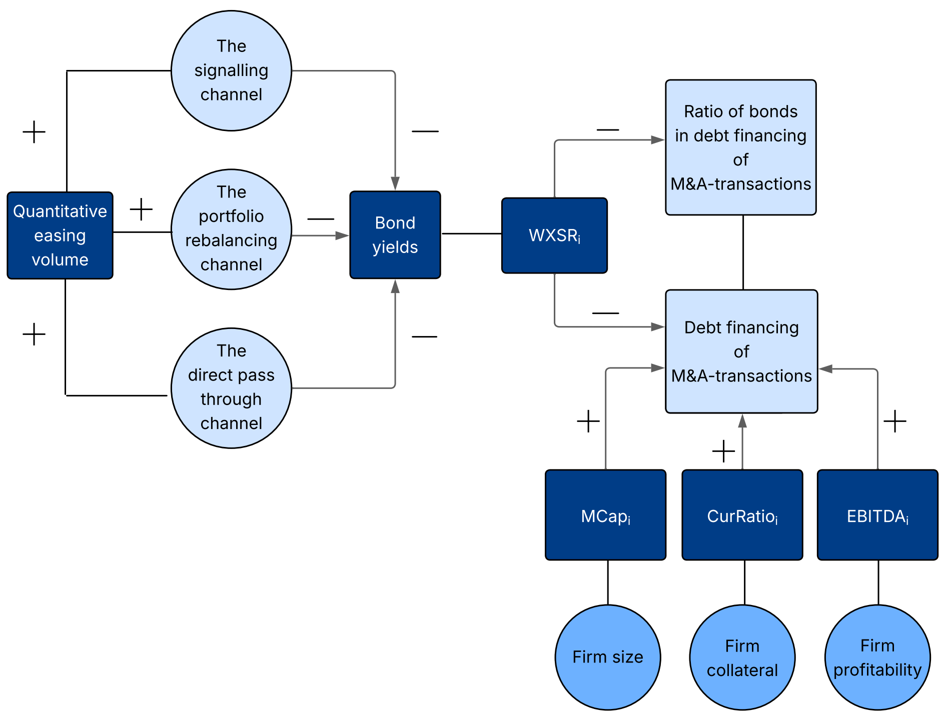

Figure 1: Conceptual model of the effect of quantitative easing on the debt structure and leverage of M&A-transactions. Plus and minus signs indicate a positive or negative hypothesized relationship between factors respectively.

3 Methodology

3.1 Empirical strategy

Literature suggests that quantitative easing lowers the cost of debt, as seen by lower bond spreads. Literature also suggests that a lower cost of debt leads firms to shift away from bank loans and towards bond issuance (De Maeseneire & Brinkhuis, 2012; Grosse-Rueschkamp et al., 2019). Prior research has shown that firms take on more debt when interest rates are low, in line with the market timing theory of capital structure. Research also found that market timing plays a role in the issuance of convertible bonds by firms (Krishnaswami & Yaman, 2008). Hence, the following two hypotheses follow from literature. This leads to the following main hypothesis:

H1: Firms issue more bonds as a part of their debt structure to finance mergers and acquisitions under quantitative easing conditions.

To estimate the effect of quantitative easing on the ratio of corporate bonds in the debt structure of merger and acquisition transactions, a model derived from Grosse-Rueschkamp et al. (2019) is used. They use a similar model to measure firm leverage and capital structure with regards to monetary policy. Their model accounts for a panel dataset, but due to the cross-sectional nature of my data, the model is adjusted to fit the datastructure of this thesis. Other differences are the inclusion of the WX-shadow rate as a measure of bond prices.

The dataset contains individual observations of M&A-transactions with corresponding data of multiple acquirers at multiple different points in time, where the transaction itself is the observation. As a consequence, the data structure is cross-sectional in nature, with observations at multiple different points in time. In order to test the effect of quantitative easing on the ratio of corporate bonds in the debt structure of merger and acquisition transactions, the following regression formula is used.

$$model\ 1: B/D_i = \alpha_0 + WXSR_i + MCap_i + CurRatio_i + \epsilon_i$$

The B/D_i-variable is a ratio of bonds issued within three years by the acquiring firm before the acquisition transaction and with a maturity after the transaction, to the net total level of debt of the firm in the twelve months leading up to the transaction. $WXSR_i$ is the Wu-Xia shadow rate in the month of the transaction. $WXSR_i$ is a shadow interest rate that approximates forward rates and is correlated to macro-economic variables in a similar fashion as the federal funds rate (Wu & Xia, 2016). For this thesis, the European equivalent is used. $WXSR_i$ represents the shadow interest rate three and a half years before the transaction.

For control variables, firm size and collateral are included. The $MCap_i$-variable represents the firm size of the acquiring firm and is expressed as the 12-month market capitalization of the acquiring firm in the year before the transaction. Although corporate finance literature views acquirer profitability as one of the key factors impacting leverage in merger and acquisition transactions, a profitability variable is left out of the model due to significant multicollinearity with the firm size variable. The $CurRatio_i$-variable represents acquiring firm collateral and is expressed as the current ratio, which is the ratio of tangible assets to the net total assets of the acquiring firm in the twelve months leading up to the transaction.

Secondly, a regression is run to test whether monetary policy impacts the total leverage of acquiring firms in merger and acquisition transactions, as literature suggests that the CSPP lowers the cost of borrowing for acquiring firms and consequently resulting in more leverage in mergers and acquisitions. This result leads to the following hypothesis:

H2: Firms take on more debt to finance mergers and acquisitions under quantitative easing conditions.

$$model\ 2: D/E_i = \alpha_0 + WXSR_i + MCap_i + CurRatio_i + \epsilon_i$$

In model 2, the dependent variable D/E_i-variable represents firm leverage and is expressed as the debt-to-EBITDA-ratio of the acquiring firm in the 12 months before the transaction. As the effect of monetary policy on acquirer leverage is lagged in practice, the $WXSR_i$-variable is the Wu-Xia shadow rate half a year before the transaction. For control variables acquirer size and acquirer collateral are included. $MCap_i$ is expressed as the 12-month market capitalization of the acquirer, and acquirer collateral $CurRatio_i$ is expressed as the 12-month tangible asset/total asset-ratio.

3.2 Definition of variables and concepts

3.2.1 Dependent variables

In order to measure the ratio of bonds in debt financing, a proxy variable had to be created. As neither the university nor the internet has access to exact levels of outstanding bonds on specific days, a proxy for the role of bonds in financing mergers and acquisitions had to be constructed. This was done by taking the total value of all bonds issued with a maturity after the transaction, in the three years in advance to the transaction, by the acquiring firm corresponding to the transaction. The window of three years is chosen as a larger window that guarantees that funds raised by the issuance of the bonds were used to finance other projects. A window smaller than three years led to even tighter data constraints to the point where reliable statistical analysis was no longer possible, as already very few debt instrument-financed transaction acquirers issued bonds to acquire external financing in the period before the transaction. Finally, the maturity date after the transaction was carefully chosen to guarantee that the funds raised through the issuance of bonds were not already repaid before the transaction was completed and thus were not used to finance the transaction.

In order to explain the effect of quantitative easing on firm leverage, the D/EBITDA-ratio is chosen as a dependent variable. This multiple is often used in practice and corporate finance literature in order to measure leverage, since the amount of leverage an acquiring firm can borrow depends on its cash flow to repay the debt (Axelson et al., 2013; De Maeseneire & Brinkhuis, 2012).

3.2.2 Independent variables

Central bank policy rates are often used as a proxy for monetary policy in literature, as they are a good indicator for monetary policy actions (Bernanke & Blinder, 1990). However, these policy rates depend on a real-world interest rate. As Quantitative easing programs are employed in situations where the central bank is already near zero, it is difficult to measure the extent of the impact of monetary policy through policy rates, when these policy rates are near zero. To combat this difficulty, the WX-shadow rate is used to proxy monetary policy near the zero lower bound. The WX-shadow rate is an approximated forward rate that shows similar correlations to macro-economic variables as the Federal funds rate, a rate often used to measure the impact of monetary policy when interest rates are not near the zero lower bound (Wu & Xia, 2016). This variable is also calculated for the European equivalent to the Federal funds rate, the marginal lending rate. In this model, the European WX-shadow rate is used, as this thesis focuses on the European M&A-market.

In order to be able to properly attribute the effect of debt market conditions on the level of leverage of the acquirer in a merger or acquisition, firm-specific characteristics need to be accounted for. These firm specific characteristics are variables often used in corporate finance literature to proxy firm specific characteristics (De Maeseneire & Brinkhuis, 2012). These variables are firm size, profitability, and debt collateral (Rajan & Zingales, 1995). Firm size and profitability are chosen as larger firms often have easier access to debt, as well as lower pre-bankruptcy costs, associated with higher debt levels. Besides, smaller firms have fewer resources to issue bonds (Ang et al., 1982; Kanda et al., 2025). The size variable is chosen to account for the fact that lower pre-bankruptcy costs have a positive relationship with debt levels. The collateral variable is chosen since higher collateral levels increase firm debt capacity (Rajan & Zingales, 1995).

4 Data

4.1 Collection strategy

To test how monetary policy impacts the ratio of bonds in debt financing under quantitative easing conditions, a proprietary dataset is created. The M&A-module in the LSEG Workspace was used to identify all completed merger and acquisition transactions done by European acquirers that were financed with debt instruments in Europe within the timeframe that the WX-shadow rate was calculated for in the European Union. Through this M&A-module, data on transaction date, 12-month EBITDA-, 12-month Market Capitalization-, 12-month net total debt-, 12-month current assets- and 12-month total asset-variables were acquired, as well as the acquirer's name, country of origin, and their respective ISIN-code. After filtering for missing observations this strategy yielded around 261 transactions.

Unfortunately, this list only allowed for filtering all merger and acquisition transactions that were financed with some form of a debt product. It could thus not be concluded that all transactions were financed with bonds. Using Acquiror ISIN-codes, a list of all bonds issued by all acquirers in their existence was acquired, containing around 13600 individual bonds. For these bonds, their respective issue date, maturity date and issue value were acquired. Using STATA, these bonds were filtered on whether their issue date was within three years of the transaction date and their maturity date was after the transaction date and matched to the respective acquiring firm. This strategy yielded 101 transactions. Unfortunately, the issue amounts were in their native currency. Using the ECB datalab, the respective exchange rates for each bond at the issue date was acquired manually and used to calculate the issue amount for each bond in Euros. The total issued value of the bonds issued within three years before the transaction were then totaled up to come to the proxy for bond financing B_i.

As daily calculations of the WX-shadow rate were not available, the WX-shadow rate was acquired for different lags to the transaction date. These lags are six months, one year, three years, three and a half years and four years to the month of the transaction. All these lagged WX-shadow rates were manually matched to the corresponding transaction.

4.2 Data preparation

Transactions that were financed with debt instruments by acquirers that issued bonds in the three-year period leading up to the transaction but returned a total value of zero were inspected manually in order to see if the value of zero was due to omitted data in LSEG Workspace. After inspection, issued bonds in the three-year period with maturities after the transaction were added manually to the dataset. If the value of bonds was still zero after manual inspection they were filtered out, as it could not be guaranteed that these transactions were financed using bonds. This yielded a total of 61 transactions and acquirors for which can be said that they were in some way financed using bonds.

The current ratio, which represents the acquirer's collateral, was formed from the 12-month current assets divided by the 12-month total assets. The B/D-ratio was formed from the total value of bonds issued in the three years before the transaction divided by the 12-month net debt. The D/E-ratio was calculated by dividing the 12-month net debt over the 12-month EBITDA.

The dataset displayed large scale differences within variables between observations and variables, as seen in the observation scatterplots in figure 3. Since large scale differences could lead to skewed results, causing the mean effect of the independent variable to be lower than theory expects it to be, due to an increased impact of high values. Hence, the dependent variables and firm size variables were log-transformed.

4.3 Descriptive statistics

Table 1: summary statistics

Variable	Number of obs.	Mean	SD	Min	Max
log_BD	61	1.08	2.14	-3.81	10.29
log_DE	61	1.56	1.37	-0.17	6.71
CurRatio	61	0.30	0.17	0.02	0.66
log_MCap	61	8.72	2.04	3.16	12.70
WXSR	61	-2.36	3.43	-7.72	4.28

The summary statistics for the dataset are displayed in table 1. The table displays some figures that require explanation. The first figures of interest are the negative minimum value of the log-transformed variables log_BD and log_DE. Due to the way that LSEG Workspace calculates the net total debt, it is possible that acquiring firms have a negative net total debt in the year of the acquisition. This observation creates a negative BD-ratio. Since acquiring firms could have negative earnings in the year of the M&A transaction, a negative D/E-ratio is not an extraordinary result. These ratios are log transformed using a log(1+x) function to log-transform data that could be zero. As a result of using this function, the log transformation of a value between 0 and minus one returns a negative log-transformed value. However, when looking at the observation distributions in figure 3, these negative values appear to be unproblematic exceptions. However, since three log-transformed values of the BD-ratio are negative, these values cannot be used in the regression analysis by R, leaving 57 observations usable for analysis.

A final observation of interest is that the mean WX-shadow rate is negative. But economically, this can be explained by the fact that many observed M&A-transactions took place in periods where central banks used expansionary policy to boost the economy, such as during the quantitative easing programs, the global housing market crisis, and the Euro-crisis. This observation is reflected in figure 2.

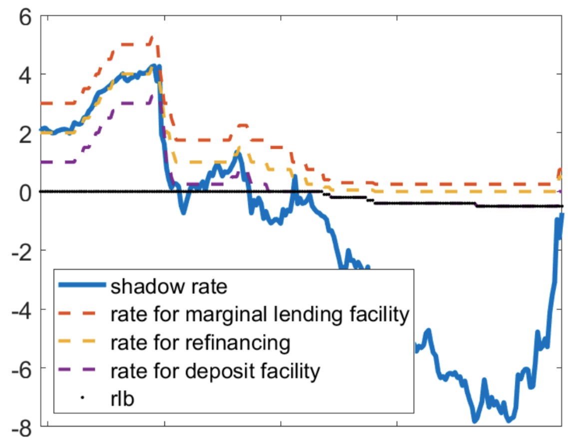

Figure 2: WX-shadow rate for the European Union 09/2004-08/2022

Upon taking a closer look at the observation scatter plots of all variables of interest, more information on data structure comes to light. The distributions of log_BD- and log_DE-variables show some observations with very high values, but interestingly, these are not the same acquiring firms. This suggests that some of the firms with extreme values issue a lot of bonds in relation to their total debt or are highly leveraged with bank debt as opposed to public debt. This could be explained by the fact that these firms operate in bond-intensive sectors such as banking. Another possible explanation lies in the fact that these firms could be large firms, with fewer constraints to access public debt financing . This explanation is reflected in the log_MCap scatter plot.

As mentioned before, the scatter plots of log_MCap and log_EBITDA closely resemble each other. This has both an economical and statistical implication. These similarities suggest that firms with a high market capitalization have high earnings before interest, tax, depreciation and amortization. This makes sense, as firm valuation often strongly relies on firm earnings. Statistically, this is likely to result in multicollinearity in a model that includes both variables.

Finally, there appears to be strong autocorrelation in the shadow rate for merger and acquisitions. However, this autocorrelation is to be expected, as the observed M&A-transactions are arranged chronologically in the dataset. This order is also used in the scatter plots for the WX-shadow rate. This distribution should not be problematic.

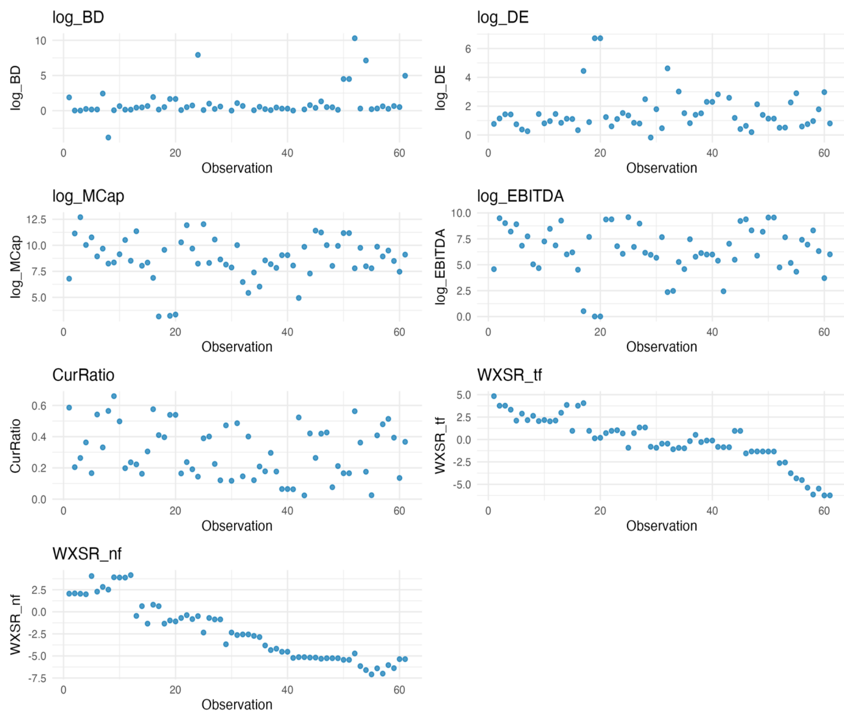

Figure 3: Scatter plots for observations of dependent and independent variables.

4.4 OLS-assumption testing

Testing the data and model for the benchmark model, the independent variables have a linear relationship with the dependent variable. Upon inspection of the observation scatter plots, the model proposed by literature showed potential signs of multicollinearity. The potential multicollinearity was visible between the log_Mcap and log_EBITDA variables. After testing for correlation, these variables showed a vif-value of 11,95 and 11,87 respectively. These values are far above the threshold of 3, proving the suggested significant multicollinearity. The log_MCAP variable was chosen instead of the log_EBITDA variable, since the model that included log_MCap as a variable had more explanatory power, as reflected by a higher adjusted R-squared.

After testing the multicollinearity of the new model, log_MCap, CurRatio and WXSR variables returned a vif-value near 1, indicating that there are no multicollinearity issues in the model. The Breusch Pagan-test indicated a BP-value of 3.1063 with a p-value of 0.3755. This result means that the null hypothesis of homoscedasticity cannot be rejected. Consequently, there is no heteroskedasticity in the model.

The Durbin Watson test returned a DW-statistic of 1.8249 with a p-value of 0.1883. The DW-statistic is close to 2, suggesting no autocorrelation in the model. For normality testing, a Shapiro-Wilk test is used. This test returned a test statistic of 0.73525 with a p-value of 6.805e-09. This is a statistically significant result, indicating that the null hypothesis that the data is normally distributed is rejected. This test result was somewhat expected due to the limited sample size and its ability to create normally distributed observations.

Looking at the test results for the OLS assumptions of the second model, there appears to be a linear relationship between the independent variables and dependent variables. However, after plotting the residuals, some residuals appear to be far removed from the regression line, suggesting influential extreme variables.

The vif-values for all independent variables are below 1.2, indicating that there is very little multicollinearity in the model. The Breusch Pagan-test returned a test statistic of 18.087 with a p-value of 0.000422, which means that the null-hypothesis of homoscedasticity is rejected, suggesting heteroskedasticity in the data. heteroskedasticity results in residuals that do not have constant variance, making estimates less precise. As a result, estimated values are further removed from the true population value.

The Durbin Watson-test returned a statistically significant at the 95% level with a p-value of 0.01401 and test statistic of 1.4872, which results in a rejection of the null hypothesis that states that the model does not have autocorrelation, with the test statistic of 1.4872 indicating positive first-order autocorrelation. Positive first order autocorrelation could lead to underestimated standard errors. However, positive autocorrelation is expected to be in the model to a certain degree, as all observations are done within the European Union or even in the same nation, under similar or the same legislation, with many variables in a relatively short time span. This exposes the variables to the same economic conditions and legislation to a large degree, suggesting a degree of correlation of variables to themselves. The Shapiro-Wilk normality test returned a p-value of 1.617e-9, which means we reject the null-hypothesis of normality in the dataset, indicating that the data is not normally distributed.

The pooled-OLS regression assumes normality for reliable statistical analysis. As mentioned, my analysis is likely limited by a small sample size. If the sample size is too small, key results might not be statistically significant where theory expects them to be. This is due to the fact that 57 unique observations remain from the dataset. The small sample size is likely to be the root of normality issues in the dataset, as shown by the Shapiro-Wilk test for the benchmark model and the secondary model. This means that the reliability of the analysis could be compromised. In order to combat issues arising from the limited sample size, bootstrap analysis is done. This technique uses resampling with layback form existing observations to estimate the true distribution of observations, with the purpose of simulating a larger sample size. The existing 57 observations will be resampled 10000 times, as this is a reliable amount of resampling that R can still handle. Bootstrapping combats the normality issues in the model and enables me to make reliable assumptions about the underlying dataset based on theory.

The pooled-OLS regression assumes no autocorrelation in the data. If the model has autocorrelation, estimated standard errors might be too low, which could lead to false conclusions about the significance of explanatory variables. As shown by the Durbin Watson-test, there appears to be positive first-order autocorrelation in both models. The autocorrelation is also visible in the scatter plots for the log_MCap- and log_EBITDA-variables. In order to counteract the autocorrelation, the log_EBITDA variable is removed from the pooled OLS-regression. A model that included the log_MCap-variable appeared to have more explanatory power, as reflected by the higher R-squared value in that model.

Finally, the pooled-OLS regression assumes homoscedastic data. If the model does not have homoscedastic data, errors do not have the same variance for all observations. This means that the OLS no longer has minimum square error. Heteroskedasticity is present in model two, as shown by the Breusch-Pagan test. The model is not homoscedastic. To combat these heteroskedasticity issues, robust standard errors are used in model two.

4.5 Bootstrap distribution testing

In order to be able to get robust results of the relationship between quantitative easing and the ratio of bonds in the debt structure in mergers and acquisitions results based on resampled data, the underlying resampling distributions should be reliable. Upon closer inspection of the bootstrap distributions in figure 4 and 5. In the bootstrap distribution of the benchmark model in figure 4, all mean-centered distributions appear to be relatively symmetrical, suggesting a relatively stable estimate without influence of outliers. Only the 3,5-year lagged WX-shadow rate appears to be slightly biased by low values. The distribution of resampled observations is relatively wide for the collateral variable, suggesting some uncertainty in the estimation of the relationship between firm collateral and the ratio of bonds in debt financing of mergers and acquisitions. The distributions for the firm size and 3,5-year lagged shadow rate and firm size are relatively narrow in the bottom distribution, suggesting robust results.

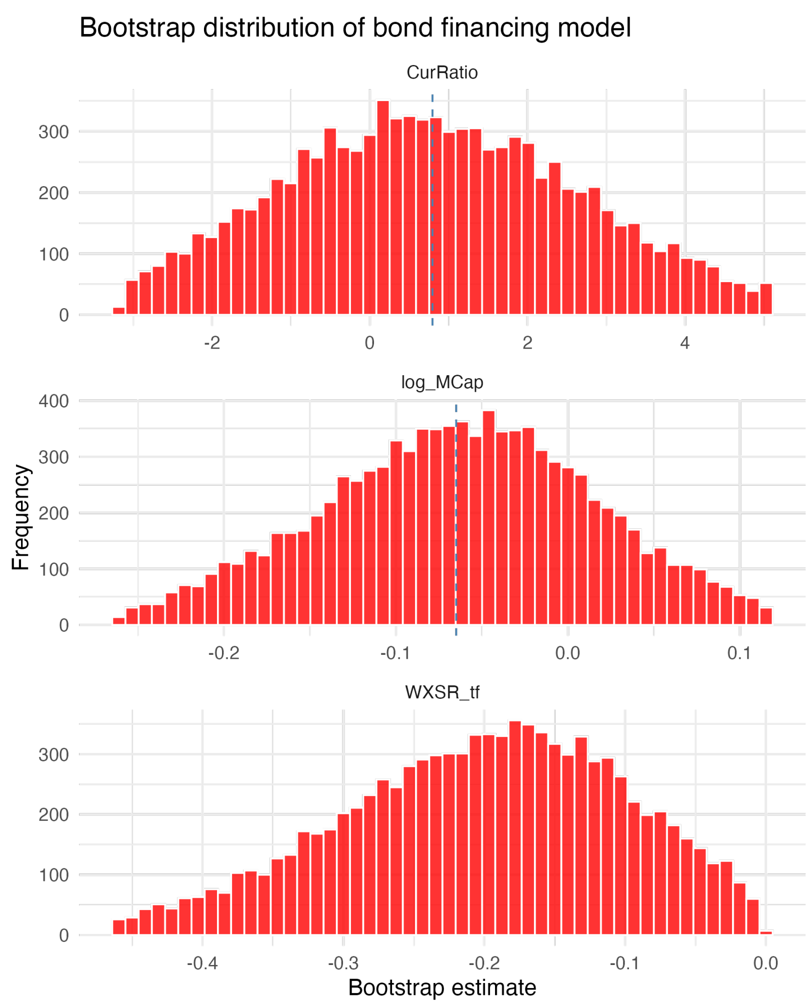

Figure 4: Resampling distributions of benchmark model

Upon closer inspection of the underlying bootstrap distribution for the second model in figure 5, the distribution of resampled observations appears symmetrical, suggesting very little to no impact from outliers, except for the firm size variable. The firm size variable has a fat right tail, suggesting that the estimated relationship is somewhat impacted by larger firms. The distribution of resampled observations of the firm collateral appears to be relatively wide, suggesting some uncertainty of the estimation of the relationship between acquirer collateral and leverage in mergers and acquisitions. The distribution of observations for the half-year lagged WX shadow rate and market cap are narrow, suggesting robust results. According to the symmetry and shape of these bootstrap distributions, 10.000 resamples based on 57 observations appear to be sufficient to make a reliable resampling distribution with little to no bias and robust results.

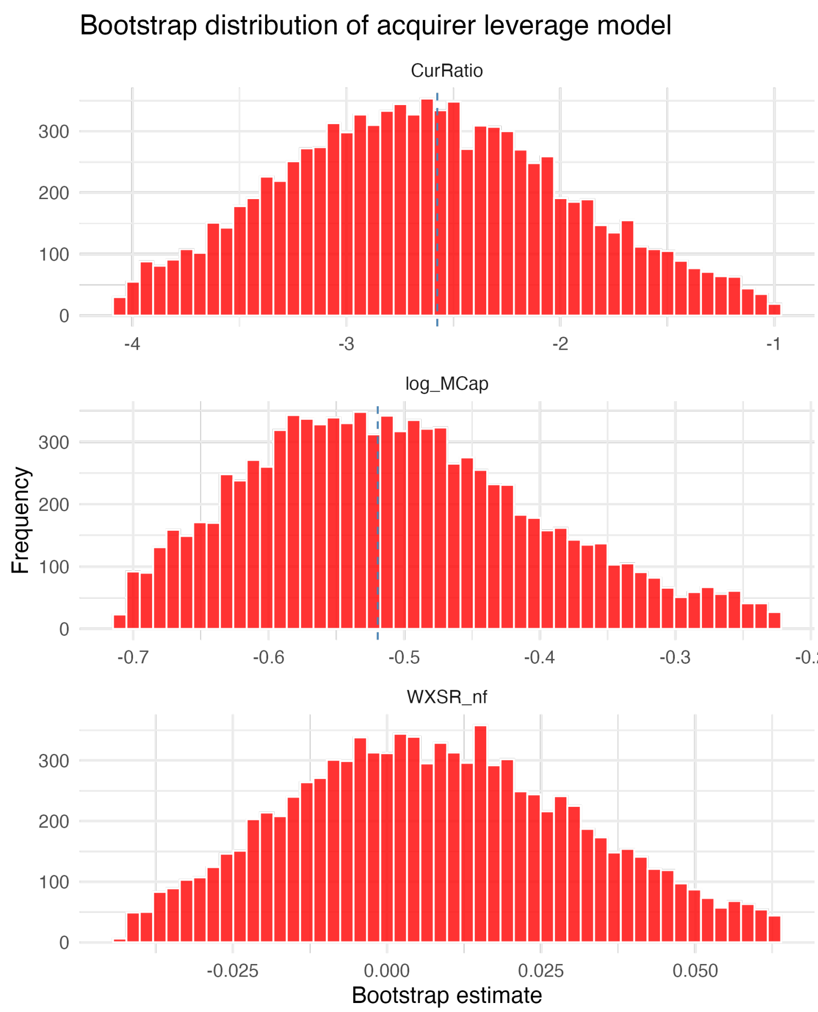

Figure 5: Resampling distributions of model 2

5 Results

5.1 Benchmark results

Table 2: Effect of quantitative easing on debt structure and leverage in merger and acquisition transactions

	Acquirer bond financing	Acquirer leverage
Dependent variable	**B/D_i**	**D/E_i**
Monetary policy effects		
WXSR (t - 3,5)	-0,201**	
WXSR (t - 0,5)		-0.005
Firm characteristics		
Acquirer firm size	-0.065	-0.380***
Acquirer collateral	0.795	-3.102***
(Intercept)	1.409	5.691***
Number of obs.	57	57
Number of resamples	10000	10000

*Dataset includes observations of 57 European merger and acquisition transactions from November 1st, 2004, until May 30th, 2022. The D/E_i -bootstrap model is run with robust standard errors. Acquirer bond financing-, Acquirer leverage- and Acquirer firm size- variables are log-transformed. Significance: ***1%, **5%, *10%.*

Table 2 shows the results of the bootstrap analysis for both the debt structure and leverage models respectively. The benchmark model shows a statistically significant negative relationship between monetary policy and the ratio of bonds to debt of the acquiring firm. The results indicate that a decrease of one percent of the WX-shadow rate as a result of quantitative easing, leads to a 20,1% increase in the ratio of issued bonds to the debt of acquirers. This result is statistically significant at the 95%-level. This is in line with findings in literature on corporate bond issuance as a result of quantitative easing, by Grosse-Reushkamp et al. (2019), leverage in M&A-transactions during quantitative easing by de Maeseneire & Brinkhuis 2012), the relationship between quantitative easing and debt structure by Kanda et al. (2025) and market timing theory by Baker & Wurgler (2002). The estimates for the control variables are not significant. For the acquirer collateral control variable, this makes sense, as publicly issued corporate bonds often do not have underlying collateral. In contrast to findings on bond issuance, financing constraints and firm size by Kaya et al. (2025) and Ang et al. (1982), the estimate for the control variable for firm size is not statistically significant. According to this model, quantitative easing has a statistically significant relationship with the ratio of bonds in the debt structure of acquirers in mergers and acquisitions. According to this result, acquiring firms issue more bonds to finance merger and acquisition transactions under quantitative easing conditions. This result means we accept hypothesis 1, that states that firms issue more bonds to finance mergers and acquisitions under quantitative easing conditions.

The results of the second model indicate that when the WX-shadow rate decreases by 1% as a result of quantitative easing, leverages increase by 0,5%. However, this result is not statistically significant. According to the model, quantitative easing conditions do not increase acquirer leverage in merger and acquisition transactions. This result contradicts the findings of Adra et al. (2020), who found a negative relationship between contractionary monetary policy and leverage in M&A-transactions, as well as the market timing theory by Baker & Wurgler (2002). The effects of control variables acquirer collateral and acquirer firm size are statistically significant. Interestingly, there is a negative relationship between firm collateral, firm size and firm leverage in mergers and acquisitions according to this model. This result appears to contradict the theory that larger firms have easier access to debt financing as proposed by Modigliani and Miller (1958). Theoretically these studies can be countered by the argument proposed by Rajan & Zingales (1995), who state that a negative relationship between firm size and leverage could be explained by the fact that larger public firms have more public information available and as a consequence, outside investors prefer equity to finance these firms. Another explanation is the fact that the acquirer firm size variable is highly correlated with the profitability variable. Firms with higher profitability could be more likely to finance projects with their own funds, in line with the pecking order theory (Myers & Majluf, 1984).

The results in model two show no statistically significant relationship between quantitative easing and leverage in M&A-transactions. As a result, the second hypothesis, which states that acquiring firms take on more debt to finance merger and acquisition transactions under quantitative easing conditions, is rejected.

5.2 Robustness testing

Table 3: Effect of quantitative easing on debt structure and leverage in merger and acquisition transactions

	Acquirer Bond Financing	Acquirer Leverage
Dependent variable	**B/D_i**	**D/E_i**
Benchmark model effect of WX-shadow rate	-0.201**	-0.005
Five largest observations dropped		
WX-shadow rate	-0.021	-0.028
Acquirer firm size	-0.031	-0.172***
Acquirer collateral	0.301	-3.215***
Five smallest observations dropped		
WX-shadow rate	-0.173	0.006
Acquirer firm size	-0.074	-0.408***
Acquirer collateral	1.234	-2.607**
Number of obs.	52	52
Number of resamples	10.000	10.000

*Dataset includes observations of 57 European merger and acquisition transactions from November 1st, 2004, until May 30th, 2022. The D/E_i -bootstrap model is run with robust standard errors. Acquirer bond financing-, Acquirer leverage- and Acquirer firm size- variables are log-transformed. Significance: ***1%, **5%, *10%.*

Table 3 displays the results of the bootstrap analysis of the benchmark models, but with exclusion of either the five largest values or the five smallest values. The observation distribution graphs in figure 3 showed that even after log-transformation, around five observations returned very high values for both the B/D_i and the D/E_i-variables.

According to the results in table 3, benchmark model test results are likely to be influenced by both the five smallest and five largest observations in the dataset. The limited sample size is likely to play a role in the changes in the estimates in the robustness tests as well, as the sample changes deduct almost ten percent of the total observations in the dataset in comparison to the dataset used to test the benchmark model.

The sample robustness test results for the second model seem more robust to extreme observations. All estimates of the independent variables remain like what they were in the benchmark model for acquirer leverage. In the sample change where the 5 largest observations were dropped, the estimate for the acquirer firm size variable is about half of the value in the benchmark model. This is likely due to larger firms having fewer constraints in taking on debt and are therefore generally more highly levered than smaller firms. Taking out these large, highly levered firms leads to lower estimates of the relationship between acquirer firm size and leverage in mergers and acquisitions, as smaller firms with less leverage play a larger role in the manipulated sample. For the sample where the 5 largest observations of the D/E_i – ratio are left out, the estimate for acquirer collateral is very similar to the benchmark model, suggesting that the collateral estimate is not very susceptible to influential observations in the underlying data.

Table 4: Effect of quantitative easing on debt structure and leverage in merger and acquisition transactions with firm profitability

	(1)	(2)	(3)	(4)
Dependent variable	**B/D_i**	**D/E_i**	**B/D_i**	**D/E_i**
Benchmark model effect of WX- shadow rate	-0.201**	-0.005	-0.201**	-0.005
Monetary policy effects				
WXSR (t - 3,5)	-0.199**		-0.200**	
WXSR (t - 0,5)		0.007		0.004
Firm characteristics				
Acquirer firm size			-0.020	0.238
Acquirer profitability	-0.057	-0.379***	-0.038	-0.549***
Acquirer collateral	0.806	-2.919***	0.799	-2.866***
(Intercept)	1.204	4.830***	1.278	3.799**
Number of obs.	57	57	57	57
Number of resamples	10.000	10.000	10.000	10.000

*Dataset includes observations of 61 European merger and acquisition transactions from November 1st, 2004, until May 30th, 2022. The D/E_i -bootstrap model is run with robust standard errors. Acquirer bond financing-, Acquirer leverage-, acquirer profitability- and Acquirer firm size-variables are log-transformed. Significance: ***1%, **5%, *10%.*

Table 4 displays the main model changes. In model one and two, the benchmark model is bootstrapped with the acquirer profitability variable instead of acquirer firm size, to control for this variable being left out of the benchmark model. Similar to the benchmark model, there is still a statistically significant negative relationship between monetary policy and the ratio of bonds in the leverage of mergers and acquisitions. The benchmark control variables still have a small and statistically insignificant relationship with the ratio of bonds in the leverage of mergers and acquisitions. Due to the results of the multicollinearity and correlation testing, it was expected that acquirer profitability and acquirer firm size would have a very similar impact on the ratio of bonds in the leverage of mergers and acquisitions, and that expectation is confirmed when comparing the results of model 1 in table 4 to the results of the benchmark model in table 2.

Model 2 used acquirer profitability instead of acquirer firm size as well, only with regards to benchmark model 2. In line with expectations and model 1 in table 4, the relationship between acquirer firm size and acquirer profitability is very similar to the benchmark models, as confirmed by comparing the models in the model changes to the benchmark models. The relationships of both the acquirer collateral control variable and the shadow rate independent variable with the acquirer leverage remain very similar to the benchmark model, suggesting that the choice for acquirer firm size barely had an impact on the reliability of the benchmark model.

In model 3 and 4, the benchmark model is brought more in line with models used to explain acquirer leverage in merger and acquisition transactions in traditional corporate finance literature. For model 3, there is no difference in the significance of results and estimates. Interestingly, the total effect of acquirer firm size and profitability are extremely similar to the total effect of acquirer profitability in model 1 of the robustness check.

In model 4, both acquirer profitability and acquirer firm size are included in the leverage model. Due to the inclusion of acquirer profitability, the acquirer firm size lost its significant relationship with leverage in M&A-transactions.

Table 5: Effect of quantitative easing on debt and bond issuance in merger and acquisition transactions

	Acquirer bond issuance	Acquirer leverage
Dependent variable	**B_i**	**D_i**
Benchmark model effect of WX-shadow rate	-0.201**	-0.005
Monetary policy effects		
WXSR (t - 3,5)	-0.265**	
WXSR (t - 0,5)		0.011
Firm characteristics		
Acquirer firm size	0.575***	0.721***
Acquirer collateral	-0.980	-4.339***
(Intercept)	2.520	2.409***
Number of obs.	57	57
Number of resamples	10000	10000

*Dataset includes observations of 61 European merger and acquisition transactions from November 1st, 2004, until May 30th 2022. The D/E_i -bootstrap model is run with robust standard errors. Acquirer bond -, Acquirer debt- and Acquirer firm size- variables are log-transformed. Significance: ***1%, **5%, *10%.*

two robustness checks are done in order to confirm that there is not just a statistically significant relationship with the debt component in the benchmark model or profitability component of the second model in the dependent variable. According to the results of the robustness tests in table 5, there appears to be a statistically significant relationship between bond issuance in the period leading up M&A-transactions in general, suggesting that monetary policy does indeed increase corporate bond issuance. This relationship means that for every percent that the shadow rate decreases due to quantitative easing, bond issuance in the period leading up to M&A-transactions is increased by 0,265%. This result is statistically significant and in line with literature, as previous literature by Grosse-Reushkamp et al. (2019) found that quantitative easing increases corporate bond issuance. It is interesting to note that, in comparison to the benchmark model, acquirer firm size has a statistically significant positive relationship with bond issuance in the period leading up to M&A-transactions, suggesting that larger firms do have fewer constraints with regards to public financing, confirming the findings in studies by Ang et al. and Kaya et al. (2022). Similar to the benchmark model, the relationship between acquirer collateral and bond issuance in the period leading up to M&A-transactions is not significant. Economically this makes sense, as in contrast to bank debt, publicly issued bonds do not have underlying guarantees such as collateral, so the amount of collateral a firm has should not influence the likelihood that it issues bonds. Thus, there should not be a relationship between firm collateral and bond issuance.

Similar to the benchmark model, there is no statistically significant relationship between quantitative easing and leverage in M&A-transactions according to this data. Control variables are still significant at the 99% level. In comparison to the benchmark model, the relationship of acquirer firm size with net total debt levels is about twice as strong as firm size and leverage. However, this is no coincidence. As the multicollinearity and correlation testing pointed out, the acquirer firm size and profitability variables are strongly correlated. It is likely that acquirer firm size has a stronger relationship with acquirer profitability than it has with net total debt levels, increasing the denominator in the leverage variable, which explains why the firm size has a stronger relationship with net total debt than it does with acquirer leverage . This leads to the conclusion that there is still a contradicting relationship between acquirer collateral and acquirer debt levels in M&A transactions.

Table 6: Effect of quantitative easing on debt structure and leverage in merger and acquisition transactions for different lagged shadow rates

	Acquirer bond issuance	Acquirer leverage
Dependent variable	**B/D_i**	**D/E_i**
Benchmark model effect of shadow rate	-0.201**	0.005
Monetary policy effects		
WXSR (t = 0)		0.010
WXSR (t - 1)		-0.003
WXSR (t - 3)	-0.169*	
WXSR (t - 4)	-0.178	
Number of obs.	57	57
Number of resamples	10.000	10.000

*Dataset includes observations of 61 European merger and acquisition transactions from November 1st, 2004, until May 30th, 2022. The D/E_i -bootstrap model is run with robust standard errors. Acquirer bond financing-, Acquirer leverage- and Acquirer firm size- variables are log-transformed. Significance: ***1%, **5%, *10%. The benchmark policy effects are measured at 0,5 years before bond issuance and transaction respectively (t-3,5 and t-0,5).*

Table 6 displays the bootstrap results for lagged WX-shadow rates at 2 different relevant moments in time for both bond issuance and leverage models. In the bond issuance model, the benchmark model is run with the WX-shadow rate at different moments before the benchmark for the start of the bond issuance. As the start of the period for which issued bonds are presumed to finance the merger or acquisition is three years before the completion of the M&A transaction, this three-year period is taken as a benchmark for the effect of the shadow rate. As visible in table 6, there is still a statistically significant negative relationship between monetary policy and the amount of bond in the debt structure of an M&A-transaction, at the start of the period in which bond issuance is measured. This means that for every unit that the shadow rate decreases as a result of asset purchases under the CSPP, the ratio of bonds to total debt in M&A-transactions increases by 0,169%. This result is expected and in line with the benchmark model and theory. However, the effect is weaker and less statistically significant, at 10%. Economically this makes sense, as monetary policy often requires some time to impact the economy, which means that the impact of monetary policy on the economy is often lagged. The WX-shadow rate at three years before the transaction should still impact bond issuance before M&A-transactions, but there is likely to be a weaker impact on overall bond issuance. This is likely since bond issuance immediately after t-3 is not yet affected by monetary policy at t-3, but by monetary policy at an earlier point in time, due to the lagged impact of monetary policy. which makes sense statistically as well. According to these results, it is very likely that monetary policy closer in time to the M&A-transaction, has a stronger relationship with bond issuance even closer to the transaction date. As for the shadow rate at t-4, which is the shadow rate four years before the M&A-transaction and one year before the issuance of bonds is measured, there no longer appears to be a statistically significant effect of monetary policy on bond issuance. Although issuing bonds on the primary markets takes time, according to these results, monetary policy does not impact bond issuance with the purpose of financing M&A-transactions at least a year later. According to these results, the effect of monetary policy on bond issuance to finance M&A transactions is both lagged and temporary. This effect could be due to the fact that firm managers do not take monetary policy from the past into account in the decision process leading up to bond issuance, but rather look at monetary policy at that moment.

As for model 2, the monetary policy stances in the month of the transaction as well as the year before the transaction do not seem to impact acquirer leverage levels in the M&A-transaction, which is in line with the benchmark model, but still contradicts theory. A possible explanation is that firm managers do not take asset purchases into account specifically when deciding on the amount of leverage in M&A transactions, but only look at the monetary policy landscape as a whole.

In this section, I found a statistically significant relationship between monetary policy and the ratio of bonds in the debt structure of mergers and acquisitions. This result is susceptible to sample changes but is robust with regards to model changes and WX-shadow rate lag changes. According to this data, there is no evidence of a statistically significant relationship between monetary policy and acquirer leverage in merger and acquisition transactions.

6 Conclusion and discussion

6.1 Conclusion

This study examined the relationship between Quantitative easing and the use of corporate bonds as part of acquirer leverage in M&A transactions in the European Union, using a proprietary pooled cross-sectional dataset on European merger and acquisition transactions. As quantitative easing is associated with a lower cost of debt and lower bond yields, firms are expected to take on more debt and issue more bonds to finance projects. In line with this logic, a model is constructed to test the relationship between quantitative easing and corporate bonds that were issued in the period leading up to the transaction.

Regression analysis results indicate a negative relationship between the WX-shadow rate as a proxy for monetary policy and the ratio of bonds to debt levels of acquiring firms, suggesting that a higher purchase volume under quantitative easing programs increases the ratio of bonds in the debt structure of M&A-transactions. Besides this, no evidence was found for a relationship between increased levels of leverage and quantitative easing.

These results help explain how monetary policy impacts the European M&A-market. More specifically, it guides and helps the managers of acquiring firms, financial and legal professionals in understanding the effect of monetary policy on financial structure decisions in M&A-transactions. Besides, these results help central banks in better understanding the impact of their policy decisions in practice, specifically with regards to mergers and acquisitions.

6.2 Discussion

The analysis faced a major limitation in the availability of data. Since acquirers are not obligated to disclose how merger and acquisition transactions are financed, it is difficult to say if, and to what extent, merger and acquisition transactions are financed with bonds issued ahead of M&A-transactions. This issue is also visible in literature, as few quantitative studies relate funds raised with bonds to specific projects. On top of that, bond issuers do not always disclose which projects they intend to finance with the bonds that they issue, meaning that it cannot be said for certain that bonds issued in the period leading up to merger and acquisition transactions are issued with the purpose of financing a transaction. The availability of data and the reliability of available data was limited. These predicted data issues also became visible when testing the dataset and models, which brought normality-, autocorrelation- and homoscedasticity- issues to light. The data constraints could be counteracted in future studies by taking larger areas into consideration, by looking at the global M&A-market, or by looking at markets with more available data or stricter transaction information disclosure policies. Branching out to other areas also expands the timeframe for which M&A-transactions are taken into consideration, as the WX-shadow rates are calculated for a longer period for the United States and the United Kingdom, which could relieve data constraints to a further extent. Another recommendation to combat data constraints in future studies could be the use of regular marginal facility interest rates as an approximation of monetary policy in periods that these rates are not near zero. This extends the period for which M&A-transactions are measured in comparison to this study artificially, increasing sample size at the cost of using two slightly different interest rates as an approximation for the same monetary policy variable.

Future research could also improve upon the variable selection in the models used in this thesis. The models in this thesis use variables derived from corporate finance literature on M&A-leverage as control variables to explain the effect of quantitative easing on leverage and bond issuance. However, model testing showed high correlation and multicollinearity-issues between the size- and profitability-variables, which were solved after removing the profitability variable. Choosing another variable for firm size, such as acquirer 12-month total assets, with lower correlation to profitability to approximate firm size could resolve these multicollinearity issues, creating a model that reflects literature closer than what the model in this thesis does. Furthermore, control variables for the leverage model and bond financing model, which were hypothesized to be control variables for both, were not statistically significant in the bond financing model, suggesting different model specification with regards to the benchmark model.

The choice of the WX-shadow rate as an approximation of quantitative easing could compromise results as well, as theory states that this policy rate approximates all monetary policy near the zero lower bound, suggesting that its approximation consists of the effect of other monetary policy as well. This could mean that the effect of quantitative easing is dampened or amplified in comparison to its real-world influence. Future papers could improve upon this study by looking at the issue date of each bond is issued in the period leading up to the transaction and considering the WX-shadow rate in the period in advance of the issuance of the bond in order to get a more sophisticated approximation of monetary policy around the time of the bond issuance.

To get a more precise estimation of the effect of quantitative easing, future studies could focus their research design on M&A-transactions in specific sectors. Certain sectors, such as the banking sector, use more bond financing to meet their capital needs than others, which makes it interesting to study differences due to quantitative easing between sectors, as the effects of quantitative easing might not be as strong for every sector.

As mentioned, this thesis faces several limitations. This is partially since, to my knowledge, this is the first study that relates quantitative easing to the ratio of bonds in financing M&A-transactions and is rather explorative in nature. This study could act as a foundation for future research. Studying this overlap in the corporate finance and the monetary policy fields is imperative, since monetary policy conditions are proven to impact corporate decision-making in general, and financing choices in mergers and acquisitions specifically. Given the aforementioned limitations, this thesis still finds a relationship between quantitative easing and debt levels in merger and acquisition transactions, but no relationship between quantitative easing and bond financing of mergers and acquisitions.

7 Bibliography

Adra, S., Barbopoulos, L. G., & Saunders, A. (2025). The fed information shocks and the market for corporate control: Predictive and causal effects. *Journal of Corporate Finance*, *90*, 102681. https://doi.org/10.1016/J.JCORPFIN.2024.102681

ANG, J. S., CHUA, J. H., & MCCONNELL, J. J. (1982). The Administrative Costs of Corporate Bankruptcy: A Note. *The Journal of Finance*, *37*(1), 219–226. https://doi.org/10.1111/j.1540-6261.1982.tb01104.x

Axelson, U., Jenkinson, T., Strömberg, P., & Weisbach, M. S. (2013). Borrow Cheap, Buy High? The Determinants of Leverage and Pricing in Buyouts. *Journal of Finance*, *68*(6), 2223–2267. https://doi.org/10.1111/jofi.12082

Baker, M., & Wurgler, J. (2002). Market Timing and Capital Structure. *The Journal of Finance*, *57*(1).

Beaudry, P., Caglayan, M., & Schiantarelli, F. (n.d.). *Monetary Instability, the Predictability of Prices, and the Allocation of Investment: An Empirical Investigation Using U.K. Panel Data*.

Bernanke, B., & Blinder, A. (1990). *The federal funds rate and the channels of monetary transmission*.

Carlino, G., & DeFina, R. (1999). The differential regional effects of monetary policy: Evidence from the U.S. states. *Journal of Regional Science*, *39*(2), 339–358. https://doi.org/10.1111/1467-9787.00137

Chen, L.-J., & Chen, S.-Y. (2011). *How the Pecking-Order Theory Explain Capital Structure*.

De Maeseneire, W., & Brinkhuis, S. (2012). What drives leverage in leveraged buyouts? An analysis of European leveraged buyouts' capital structure. *Accounting and Finance*, *52*(SUPPL.1), 155–182. https://doi.org/10.1111/j.1467-629X.2011.00431.x

'Fischer, J., & 'Horn, C.-W. (2021). Monetary Policy and Mergers and Acquisitions∗. *Beiträge Zur Jahrestagung Des Vereins Für Socialpolitik 2021: Climate Economics*.

Gamba, A., & Triantis, A. (2008). The value of financial flexibility. *Journal of Finance*, *63*(5), 2263–2296. https://doi.org/10.1111/j.1540-6261.2008.01397.x

Grosse-Rueschkamp, B., Steffen, S., & Streitz, D. (2019). A capital structure channel of monetary policy. *Journal of Financial Economics*, *133*(2), 357–378. https://doi.org/10.1016/J.JFINECO.2019.03.006

Jansen, D. W., Kishan, R. P., & Vacaflores, D. E. (2013). Sectoral Effects of Monetary Policy: The Evidence from Publicly Traded Firms. *Southern Economic Journal*, *79*(4), 946–970. https://doi.org/10.4284/0038-4038-2011.040

Jiménez, G., Ongena, S., Peydró, J.-L., & Saurina, J. (2014). Hazardous Times for Monetary Policy: What Do Twenty-Three Million Bank Loans Say About the Effects o. *Econometrica*, *82*(2).

Kanda, J. F., Pinto, J. M., & Silva, B. P. (2025). The ECB's APP's impact on non-financial firms' cost of borrowing and debt choice. *Journal of Financial Stability*, *77*, 101387. https://doi.org/10.1016/J.JFS.2025.101387

Krishnaswami, S., & Yaman, D. (2008). The role of convertible bonds in alleviating contracting costs. *The Quarterly Review of Economics and Finance*, *48*(4), 792–816. https://doi.org/10.1016/J.QREF.2007.03.005

Longstaff, F. A., Mithal, S., & Neis, E. (2005). Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market. In *Journal of Finance* (Vol. 60, Issue 5, pp. 2213–2253). https://doi.org/10.1111/j.1540-6261.2005.00797.x

Modigliani, F., & Miller, M. H. (1958). *The Cost of Capital, Corporation Finance and the Theory of Investment* (Vol. 48, Issue 3).

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, *13*(2), 187–221. https://doi.org/10.1016/0304-405X(84)90023-0

Obonyo, T. (2022). Monetary policy and cross-border acquisitions. *Finance Research Letters*, *50*, 103197. https://doi.org/10.1016/J.FRL.2022.103197

Rajan, R. G., & Zingales, L. (1995). What Do We Know about Capital Structure? Some Evidence from International Data. *The Journal of Finance*, *50*(5), 1421–1460.

Remolona, E. M., Amato J. D. (2003). *The credit spread puzzle - BIS Quarterly Review, part 5, December 2003*. https://ssrn.com/abstract=1968448

Shyam-Sunder, L., & C. Myers, S. (1999). Testing static tradeoff against pecking order models of capital structure. *Journal of Financial Economics*, *51*(2), 219–244. https://doi.org/10.1016/S0304-405X(98)00051-8

Warner, J. B. (1977). Bankruptcy, absolute priority, and the pricing of risky debt claims. *Journal of Financial Economics*, *4*(3), 239–276. https://doi.org/10.1016/0304-405X(77)90002-2

Wu, J. C., & Xia, F. D. (2016). Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound. *Journal of Money, Credit and Banking*, *48*(2–3), 253–291. https://doi.org/10.1111/jmcb.12300

Zaghini, A. (2019). The CSPP at work: Yield heterogeneity and the portfolio rebalancing channel. *Journal of Corporate Finance*, *56*, 282–297. https://doi.org/10.1016/J.JCORPFIN.2018.12.004

Appendix A: Statistical tests

	Benchmark model			Leverage model		
	Test statistic		p-value	Test statistic	p-value	
No autocorrelation						
Durbin-Watson test	1.8249		0.1883	1.4872	0.01401**	
normality						
Shapiro-Wilk test	0.73525		6.805e-09***	0.92652	0.001746**	
homoscedasticity						
Breush-Pagan test	3.1063		0.3755	18.087	0.000422***	
multicollinearity	Firm size	Firm collateral	WX-shadow rate	Firm size	Firm collateral	WX-shadow rate
Vif-test	1.049	1.062	1.012	1.052	1.100	1.049

Appendix B: use of generative AI

"This appendix provides a detailed account of the use of Generative AI tools during the development and writing of this thesis. These tools were used to support coding, data analysis, ensuring clarity and precision in the presentation of findings. All outputs generated were critically evaluated and, where necessary, modified by myself to align with the objectives of this research."

Coding and Data Analysis

- Description
    - Tool: ChatGPT (OpenAI)
    - Purpose: ChatGPT was used for writing, improving, and debugging R code related to regression analysis, data transformation, bootstrapping, assumption testing, and the creation of visualizations. It assisted in writing scripts for robust regression models, applying log transformations, handling outliers, and generating formatted summary tables and plots for exploratory analysis.
    - My Role: I used the AI as a programming assistant to translate statistical ideas into functional R code. Consequently, All output was carefully reviewed, modified to suit the structure of my dataset, and validated through diagnostic checks and model interpretation. I made all analytical decisions independently, and ChatGPT mainly helped me implement them correctly and efficiently.
    - My Reflection: Using ChatGPT significantly improved my coding skills in R dramatically, especially in data cleaning, regression modeling, and visual reporting. In later stages of the thesis, I was able to independently reproduce similar analyses without AI assistance. ChatGPT served as a valuable tutor that helped me better understand the logic behind each statistical approach and programming step.

- Applied in sections 4 for all data transformation and assumption testing and in section 5 for all regression analysis, robust regression analysis, bootstrap results and robustness checks.

data visualization

- Description:
  - Tool: ChatGPT (GPT-4)
  - Purpose: ChatGPT was used to generate and refine R code for creating various data visualizations, such as scatter plots, histograms, and distribution charts. The tool helped translate descriptive needs into executable R code, including enhancements for aesthetics like titles, axis labels, and layout. The visualizations were then produced and customized in R.
  - My Role: I used the AI-generated code as a foundation and critically reviewed all outputs. The final visualizations were edited and tailored to fit the specific requirements of the analysis and the formatting guidelines of the thesis.
  - My Reflection: AI significantly reduced the time I would otherwise spend searching for correct code snippets, allowing me to focus more on experimenting with different visual formats and improving the quality and clarity of the graphs.
  - Applied in: Section 4 for figures 3,4 and 5.

AI interactions

ik heb een pooled cross sectional dataset in R, ik heb de dataset geopend in R. schrijf een code voor mij waarbij ik de NA's uit kolom WXSR haal

````
```r
# Verwijder rijen waar WXSR NA is
dataset <- dataset[!is.na(dataset$WXSR), ]
```
```r
library(dplyr)
````
````

```
dataset <- dataset %>%
  filter(!is.na(WXSR))
```

dankjewel! kun je nu een code schrijven waarmee ik kolom AcquirorEBITDALast12Months kan hernoemen naar EBITDA, kolom AcquirorTotalAssetsLast12Mo naar TotalAssets, kolom AcquirorCurrentAssetsLast12 naar CurAssets en AcquirorMarketValue4WeeksPr naar MCap?

```r
library(dplyr)

dataset <- dataset %>%
  rename(
    EBITDA = AcquirorEBITDALast12Months,
    TotalAssets = AcquirorTotalAssetsLast12Mo,
    CurAssets = AcquirorCurrentAssetsLast12,
    MCap = AcquirorMarketValue4WeeksPr
  )
```

✅ **2. Met base R**

```r
names(dataset)[names(dataset) == "AcquirorEBITDALast12Months"] <- "EBITDA"
names(dataset)[names(dataset) == "AcquirorTotalAssetsLast12Mo"] <- "TotalAssets"
names(dataset)[names(dataset) == "AcquirorCurrentAssetsLast12"] <- "CurAssets"
names(dataset)[names(dataset) == "AcquirorMarketValue4WeeksPr"] <- "MCap"
```

R ziet elke waarde van WXSR als een eigen onafhankelijke variabele terwijl WXSR de onafhankelijke waarde is

```r
dataset$WXSR <- as.numeric(dataset$WXSR)
```

Als je een `dataset_clean` gebruikt zoals eerder, doe je dit daar:

```r
dataset_clean$WXSR <- as.numeric(dataset_clean$WXSR)
```

🔍 Hoe weet je of het een factor is?

Je kunt dit checken met:

```r
str(dataset$WXSR)
```

Als je dan ziet: `Factor w/ 10 levels "Low","Medium",...`, dan weet je dat het fout zit. Je wilt iets als: `num [1:100] 0.42 0.38 ...`

```r
dataset$WXSR <- as.numeric(as.character(dataset$WXSR))
```

```

**ik heb schaalverschillen, ik heb de tip uitgevoerd, ik krijg deze foutcode: Error in `mutate()`:**

ℹ️ **In argument: `across(-TotalValue, scale)`.**

**Caused by error in `across()`:**

**! Can't compute column `WXSR`.**

**Caused by error in `colMeans()`:**

**! 'x' must be numeric**

**Run `rlang::last_trace()` to see where the error occurred.**

```r
# Zet alle onafhankelijke variabelen expliciet om naar numeric (na character-conversie)
dataset_scaled <- dataset_clean %>%
  mutate(across(-TotalValue, ~ as.numeric(as.character(.)))) %>%
  mutate(across(-TotalValue, scale))
```

```r
sapply(dataset_clean, class)
```

dankjewel! Ik wil van de variabelen TotalAssets en CurAssets een nieuwe variabele maken, een ratio CurAssets/TotAssets, kun je hier code voor schrijven?

```r
library(dplyr)

dataset <- dataset %>%
  mutate(CurRatio = CurAssets / TotalAssets)
```

* De nieuwe variabele heet hier `CurRatio` (maar je kunt elke naam kiezen).
```

* Als `TotalAssets` op sommige rijen nul of NA is, krijg je waarschuwingen of NA's. Je kunt dan veilig delen met:

```r
mutate(CurRatio = ifelse(!is.na(TotalAssets) & TotalAssets != 0, CurAssets / TotalAssets, NA))
```

Ik heb veel 0 waarden in de afhankelijke variabele, hoe kan ik deze eruit filteren?

```r
library(dplyr)

dataset <- dataset %>%
  filter(TotalValue != 0)
```

Of in base R:

```r
dataset <- dataset[dataset$TotalValue != 0, ]
```

```r
dataset <- dataset %>%
  filter(!is.na(TotalValue) & TotalValue > 0)
```

kun je een script schrijven om al mijn variabelen te log-transformeren?

```r
```

Maak een kopie van je dataset om te bewerken

dataset_log <- dataset_scaled

Selecteer alleen de numerieke kolommen (behalve TotalValue als je die apart wilt behandelen)

numeric_vars <- sapply(dataset_log, is.numeric)

Voer log-transformatie uit op alle numerieke kolommen (behalve variabelen met nul of negatieve waarden)

Gebruik log1p() = log(1 + x) om met nullen om te gaan

dataset_log[numeric_vars] <- lapply(dataset_log[numeric_vars], function(x) log1p(x))

```

```r
# Log specifieke kolommen
dataset_log$log_TotalValue <- log1p(dataset_scaled$TotalValue)
dataset_log$log_EBITDA <- log1p(dataset_scaled$EBITDA)
dataset_log$log_MCap <- log1p(dataset_scaled$MCap)
dataset_log$log_CurRatio <- log1p(dataset_scaled$CurRatio)
dataset_log$log_Qevolume <- log1p(dataset_scaled$Qevolume)
```

> 🔍 `log1p(x)` is gelijk aan `log(1 + x)` — dit voorkomt problemen als je data nullen bevat.

🧪 Check je getransformeerde data

```r
summary(dataset_log$log_EBITDA)
hist(dataset_log$log_EBITDA, breaks = 30, main = "Log-EBITDA", xlab = "log(1 + EBITDA)")

```

kun je een script schrijven om de 7 aannames van OLS regressie te testen op mijn data?

```r
# Benodigde packages
library(lmtest)     # voor Breusch-Pagan test (heteroscedasticity)
library(car)        # voor VIF (multicollineariteit) en outlierdetectie
library(sandwich)   # voor robuuste standaardfouten
library(ggplot2)    # voor grafieken
library(nortest)    # voor normaliteitstests

# 1. Lineariteit (scatterplot residuals vs fitted)
plot(model_log$fitted.values, resid(model_log),
    xlab = "Fitted values", ylab = "Residuals",
    main = "Residuals vs Fitted")
abline(h = 0, col = "red")

# 2. Geen multicollineariteit (VIF)
vif_values <- vif(model_log)
print(vif_values)

# 3. Homoscedasticiteit (Breusch-Pagan test)
bptest_result <- bptest(model_log)
print(bptest_result)

# 4. Onafhankelijkheid van residuen (Durbin-Watson test)
dw_result <- dwtest(model_log)
print(dw_result)

# 5. Normaliteit van residuen (Shapiro-Wilk test)

```
shapiro_result <- shapiro.test(resid(model_log))
print(shapiro_result)

# Alternatief: Anderson-Darling test (via 'nortest')
ad_result <- ad.test(resid(model_log))
print(ad_result)

# 6. Geen autocorrelatie (plots van residuen)
acf(resid(model_log), main = "Autocorrelation of Residuals")

# 7. Geen invloedrijke uitschieters (Cook's distance)
plot(cooks.distance(model_log), type = "h",
    main = "Cook's Distance", ylab = "Distance")
abline(h = 4/(nrow(dataset_log)-length(model_log$coefficients)), col = "red")

# Extra: Samenvatting van model (voor overzicht)
summary(model_log)
```

schrijf een script voor een bootstrap en gebruik deze verdelingen voor het model

```r
# Packages
library(boot)

# Stel je dataset en formule in
# Bijvoorbeeld:
# dataset_log met variabelen: log_TotalValue, log_Qevolume, log_MCap, log_CurRatio, log_EBITDA
# Formule (pas aan naar jouw variabelen)
formula_boot <- log_TotalValue ~ log_Qevolume + log_MCap + log_CurRatio + log_EBITDA
```

```
# Functie om coëfficiënten te schatten (bootstrapping functie)
boot_fn <- function(data, indices) {
  d <- data[indices, ]            # bootstrap sample
  fit <- lm(formula_boot, data = d)
  return(coef(fit))               # return coefficients
}

# Voer bootstrap uit (bijv. 1000 replicates)
set.seed(123)                     # voor reproduceerbaarheid
boot_results <- boot(data = dataset_log, statistic = boot_fn, R = 1000)

# Bekijk samenvatting
print(boot_results)

# Bereken betrouwbaarheidsintervallen (bijvoorbeeld 95% percentile intervals)
boot_ci <- boot.ci(boot_results, type = "perc", index = 2) # index=2 is eerste predictor (log_Qevolume)
print(boot_ci)

# Betrouwbaarheidsintervallen voor alle coëfficiënten
coef_names <- names(coef(lm(formula_boot, data=dataset_log)))
for (i in 1:length(coef_names)) {
  cat("\nBootstrap 95% CI voor:", coef_names[i], "\n")
  print(boot.ci(boot_results, type = "perc", index = i))
}
```

R herkent de pipe operator niet, wat kan ik hier tegen doen?

✅ **Oplossing 1: Gebruik R versie ≥ 4.1.0**

De native pipe `|>` is geïntroduceerd in **R 4.1.0**. Controleer je versie met:

```r
version
```

➤ Als je versie ouder is dan 4.1.0:

* Update R naar een nieuwere versie via https://cran.r-project.org.

✅ **Oplossing 2: Gebruik `magrittr` pipe (`%>%`) als alternatief**

Als je geen recente R-versie kunt gebruiken, dan kun je `magrittr` of `dplyr` gebruiken:

```r
install.packages("dplyr")  # of "tidyverse"
library(dplyr)

iris %>% head()
```

✅ **Oplossing 3: Gebruik basis-R zonder pipes**

```r
```

Met pipe:
iris |> head()

# Zonder pipe:
head(iris)
```

Wil je dat ik jouw code herschrijf zonder `|>` of juist met `%>%`? Laat maar weten!

**kan ik ook een robuuste regressie doen in combinatie met de bootstrap intervals?**

### 1. Installeer de juiste packages

We gebruiken `MASS::rlm()` voor robuuste regressie en `boot::boot()` voor bootstrapping.

```r
install.packages("MASS")
install.packages("boot")
library(MASS)
library(boot)
```

---

2. Stel je robuuste regressiemodel in

Bijvoorbeeld met gelogde variabelen:

```r
# Robuuste regressie op je gelogde dataset
robust_model <- rlm(log_TotalValue ~ log_Qevolume + log_MCap + log_CurRatio + log_EBITDA,
data = dataset_log)

summary(robust_model)
```

```r
boot_fn_robust <- function(data, indices) {
  d <- data[indices, ]
  fit <- rlm(log_TotalValue ~ log_Qevolume + log_MCap + log_CurRatio + log_EBITDA, data = d)
  return(coef(fit))
}

# Bootstrap uitvoeren
set.seed(123)
boot_results_robust <- boot(data = dataset_log, statistic = boot_fn_robust, R = 1000)
```

4. Betrouwbaarheidsintervallen opvragen

Bijvoorbeeld voor `log_Qevolume` (index = 2):

```r
boot.ci(boot_results_robust, type = "perc", index = 2)
```

Of voor alle coëfficiënten:

```r
coef_names <- names(coef(robust_model))
for (i in 1:length(coef_names)) {

cat("\nBootstrap 95% CI voor:", coef_names[i], "\n")

print(boot.ci(boot_results_robust, type = "perc", index = i))

}

```

R is net gecrasht, het script is niet meer compleet en ik ben de datasets kwijt, hoe kan ik deze terugkrijgen?

Als je met **RStudio** werkte:

* Open **RStudio opnieuw**.

* Er verschijnt vaak automatisch een prompt zoals:

👉 *"Restore previously open source documents and workspace?"*

Klik op **"Yes"**.

* RStudio probeert dan:

* De **.RData** (werkruimte) opnieuw te laden.

* Je **.R script** of **.Rmd** documenten te herstellen (via tijdelijk opgeslagen versies).

✅ 2. **Check of er een `.RData` bestand is opgeslagen**

R slaat soms automatisch de werkruimte op.

* Ga naar de folder waar je project of script stond.

* Kijk of er een bestand is met naam:

* `workspace.RData`

* `.RData`

* Of iets als `projectnaam.Rproj` (in dat geval ook `.Rproj.user` folder controleren)
```

* Laad dit in R met:

```r
load("path/naar/.RData")
```

Je objecten (zoals `dataset_log`, `boot_results`, etc.) komen dan terug in de Environment.

✅ 3. **Zoek naar tijdelijke bestanden van scripts**

Voor scripts (`.R` of `.Rmd`):

* Ga naar je projectfolder of je gebruikersmap.
* Kijk naar bestanden als:

  * `Untitled1.R`
  * `~filename.R`
  * `filename.RtmpXYZ...`
  * Soms worden ze opgeslagen onder `C:/Users/NAAM/AppData/Local/Temp` op Windows of `/tmp` op Mac/Linux.

✅ 4. **Gebruik `.Rhistory` voor eerdere code**

RStudio houdt een **geschiedenisbestand** bij van je eerdere opdrachten.

* In je projectfolder kan een bestand `~/.Rhistory` staan.

* Laad dat in RStudio via:

```r
loadhistory()
```

Of open het handmatig in een teksteditor om code terug te halen.

✅ 5. **Voor toekomst: instellen op automatisch opslaan**

In RStudio:

* Ga naar **Tools > Global Options > General**
* Vink aan:

  * "Restore .RData into workspace at startup"
  * "Save workspace to .RData on exit"
  * "Always save history"

he chat, ik heb een kolom in mijn dataset die na het filteren met dataset <- dataset %>% filter(TotalValue != 0) nog steeds 0 waarden weergeeft in de vorm 0.000000e+00, hoe verwijder ik deze waarden ook?

```r
dataset <- dataset %>% filter(TotalValue != 0)
```

```r
```

```
dataset <- dataset %>% filter(abs(TotalValue) > 1e-10)
```

```r
str(dataset$TotalValue)
```

Als het **geen numeriek** type is (bijvoorbeeld `character`), converteer dan eerst:

```r
dataset$TotalValue <- as.numeric(dataset$TotalValue)
```

kun je mij een mooi vormgegeven summary statistics tabel script schrijven voor de dataset 'dataset_log'?

```r
# Laad benodigde package
install.packages("psych")
library(psych)

# Summary statistics
describe(dataset_log)
```

```r
# Laad package
install.packages("skimr")
library(skimr)

# Summary statistics in mooi format
skim(dataset_log)
```

```r
# Laad packages
install.packages(c("dplyr", "gt"))
library(dplyr)
library(gt)

# Bouw samenvattende tabel
summary_table <- dataset_log %>%
  summarise(across(everything(), list(
    mean = ~mean(. , na.rm = TRUE),
    sd   = ~sd(. , na.rm = TRUE),
    min  = ~min(. , na.rm = TRUE),
    max  = ~max(. , na.rm = TRUE)
  ), .names = "{.col}_{.fn}")) %>%
  pivot_longer(cols = everything(),
               names_to = c("Variable", ".value"),
               names_sep = "_") %>%
  gt() %>%
  tab_header(
    title = "Summary Statistics",
    subtitle = "Voor dataset_log"
  ) %>%
  fmt_number(columns = c(mean, sd, min, max), decimals = 2)

summary_table
```

ik krijg deze error: Error in pivot_longer(., cols = everything(), names_to = c("Variable", :
could not find function "pivot_longer" bij functie 3, fix graag

```r
# Installeren indien nodig
install.packages(c("dplyr", "gt", "tidyr"))

# Laden van packages
library(dplyr)
library(gt)
library(tidyr)

# Samenvattende tabel bouwen
summary_table <- dataset_log %>%
  summarise(across(everything(), list(
    mean = ~mean(. , na.rm = TRUE),
    sd   = ~sd(. , na.rm = TRUE),
    min  = ~min(. , na.rm = TRUE),
    max  = ~max(. , na.rm = TRUE)
  ), .names = "{.col}_{.fn}")) %>%
  pivot_longer(cols = everything(),
               names_to = c("Variable", ".value"),
               names_sep = "_") %>%
  gt() %>%
  tab_header(
    title = "Summary Statistics",
    subtitle = "Voor dataset_log"
  ) %>%
  fmt_number(columns = c(mean, sd, min, max), decimals = 2)

# Resultaat bekijken
summary_table
```

schrijf code voor het filteren van kolommen SDCDealNo, RankDate, RankValueIncNetDebtofTarg, TargetFullName, TargetMidIndustry, AcquirorMidIndustry, AcquirorPermID, AcquirorISIN, DealStatus, FinancingViaDebtSecuritiesFl, MAType, AcquirorNation, DateAnnounced uit dataset dataset_summary

```r
# Laad dplyr als dat nog niet is gebeurd
library(dplyr)


# Selecteer alleen de gewenste kolommen
filtered_dataset <- dataset_summary %>%
  select(
    SDCDealNo,
    RankDate,
    RankValueIncNetDebtofTarg,
    TargetFullName,
    TargetMidIndustry,
    AcquirorMidIndustry,
    AcquirorPermID,
    AcquirorISIN,
    DealStatus,
    FinancingViaDebtSecuritiesFl,
    MAType,
    AcquirorNation,
    DateAnnounced
  )
```

waarom staan EBITDA, MCAP en QEvolume in de kolom in plaats van de rij, fix dit?

`r

```
# Laad benodigde packages
library(dplyr)
library(flextable)
library(officer)

# Selecteer alleen numerieke kolommen
numeric_data <- filtered_datasetSummary %>%
  select(where(is.numeric))

# Maak samenvattende statistieken per variabele
summary_stats <- numeric_data %>%
  summarise(across(everything(), list(
    Mean = ~mean(. , na.rm = TRUE),
    SD   = ~sd(. , na.rm = TRUE),
    Min  = ~min(. , na.rm = TRUE),
    Max  = ~max(. , na.rm = TRUE)
  ))) %>%
  # Transponeer zodat variabelen in rijen staan
  t() %>%
  as.data.frame()

# Voeg kolomnamen toe
colnames(summary_stats) <- c("Value")

# Splits variabelenaam en statistiektype
summary_stats <- tibble::rownames_to_column(summary_stats, var = "Variable_Stat") %>%
  tidyr::separate(Variable_Stat, into = c("Variable", "Statistic"), sep = "_") %>%
  tidyr::pivot_wider(names_from = Statistic, values_from = Value)
```

```
# Optioneel: rond getallen af
summary_stats <- summary_stats %>%
  mutate(across(where(is.numeric), round, digits = 2))

# Zet om naar flextable
summary_ft <- flextable(summary_stats) %>%
  autofit()

# Maak Word-document aan en voeg de tabel toe
doc <- read_docx() %>%
  body_add_par("Summary Statistics Table", style = "heading 1") %>%
  body_add_flextable(summary_ft)

# Exporteer naar Word-bestand
print(doc, target = "Summary_filtered_datasetSummary.docx")
```

nu staat overal [[numeric]] en [[null]

```r
# Laad libraries
library(dplyr)
library(tidyr)
library(flextable)
library(officer)

# Filter enkel numerieke kolommen uit je dataset
numeric_data <- filtered_datasetSummary %>%
  select(where(is.numeric))

# Bereken summary statistics per kolom
```

```
summary_stats <- numeric_data %>%
  summarise(across(
    everything(),
    list(
      Mean = ~mean(.x, na.rm = TRUE),
      SD   = ~sd(.x, na.rm = TRUE),
      Min  = ~min(.x, na.rm = TRUE),
      Max  = ~max(.x, na.rm = TRUE)
    ),
    .names = "{.col}_{.fn}"
  )) %>%
  pivot_longer(everything(),
               names_to = c("Variable", "Statistic"),
               names_sep = "_",
               values_to = "Value") %>%
  pivot_wider(names_from = Statistic, values_from = Value) %>%
  arrange(Variable) %>%
  mutate(across(where(is.numeric), round, 2))

# Maak een flextable van de tabel
summary_table <- flextable(summary_stats) %>%
  autofit()

# Exporteer naar Word
doc <- read_docx() %>%
  body_add_par("Summary Statistics Table", style = "heading 1") %>%
  body_add_flextable(summary_table)

# Sla het bestand op
```

print(doc, target = "Summary_filtered_datasetSummary.docx")

``

dit heeft niets opgelost

```r
# Laad benodigde libraries
library(dplyr)
library(flextable)
library(officer)

# Selecteer alleen numerieke kolommen
numeric_data <- filtered_datasetSummary %>%
  select(where(is.numeric))

# Bereken de summary statistics
summary_table <- data.frame(
  Variable = names(numeric_data),
  Mean = sapply(numeric_data, function(x) round(mean(x, na.rm = TRUE), 2)),
  SD   = sapply(numeric_data, function(x) round(sd(x, na.rm = TRUE), 2)),
  Min  = sapply(numeric_data, function(x) round(min(x, na.rm = TRUE), 2)),
  Max  = sapply(numeric_data, function(x) round(max(x, na.rm = TRUE), 2))
)

# Zet om naar een mooie flextable
ft <- flextable(summary_table) %>%
  autofit()

# Exporteer naar Word
doc <- read_docx() %>%
  body_add_par("Summary Statistics", style = "heading 1") %>%
```

```
  body_add_flextable(ft)

# Bewaar het document
print(doc, target = "SummaryStatistics_filtered_datasetSummary.docx")
```

kun je ook een word document maken waarin scatterplots van de variabelen BD, DE, TotalValue, EBITDA, CurRatio, MCap, AcqNetDebt mooi worden verwerkt op basis van dataset filtered_datasetsummary?

```r
# Laad benodigde libraries
library(ggplot2)
library(officer)
library(magrittr)

# Controleer of je variabelen numeric zijn (en aanwezig)
vars_to_plot <- c("BD", "DE", "EBITDA", "CurRatio", "MCap", "AcqNetDebt")
base_var <- "TotalValue"

# Start nieuw Word-document
doc <- read_docx()

# Loop door variabelen en maak scatterplots
for (var in vars_to_plot) {
  # Controleer of beide kolommen bestaan
  if (all(c(var, base_var) %in% names(filtered_datasetSummary))) {

    # Maak de plot
    p <- ggplot(filtered_datasetSummary, aes_string(x = var, y = base_var)) +
      geom_point(alpha = 0.6, color = "steelblue") +
```

```
      geom_smooth(method = "lm", se = FALSE, color = "darkred", linetype = "dashed") +
      labs(
        title = paste("Scatterplot:", var, "vs", base_var),
        x = var,
        y = base_var
      ) +
      theme_minimal(base_size = 12)

    # Voeg toe aan Word
    doc <- doc %>%
      body_add_par(paste("Scatterplot:", var, "vs", base_var), style = "heading 2") %>%
      body_add_gg(value = p, width = 6, height = 4)
  }
}

# Bewaar het Word-document
print(doc, target = "Scatterplots_TotalValue_vs_Others.docx")
```

kun je deze scatterplots ook mooi bundelen op 1 pagina?

```r
# Laad benodigde packages
library(ggplot2)
library(officer)
library(magrittr)
library(patchwork)  # Voor het combineren van plots

# Lijst met variabelen voor de x-as
vars_to_plot <- c("BD", "DE", "EBITDA", "CurRatio", "MCap", "AcqNetDebt")
base_var <- "TotalValue"
```

```
# Genereer scatterplots
plots <- lapply(vars_to_plot, function(var) {
  ggplot(filtered_datasetSummary, aes_string(x = var, y = base_var)) +
    geom_point(alpha = 0.6, color = "steelblue") +
    geom_smooth(method = "lm", se = FALSE, color = "darkred", linetype = "dashed") +
    labs(
      title = paste(var, "vs", base_var),
      x = var,
      y = base_var
    ) +
    theme_minimal(base_size = 10)
})

# Combineer plots in een grid (2 kolommen, 3 rijen)
combined_plot <- wrap_plots(plots, ncol = 2)

# Voeg toe aan Word-document
doc <- read_docx() %>%
  body_add_par("Scatterplots: TotalValue vs andere variabelen", style = "heading 1") %>%
  body_add_gg(combined_plot, width = 6.5, height = 9)

# Opslaan
print(doc, target = "Scatterplots_1Pagina.docx")
```

ik krijg nu deze error in de laatste stap

Error in `geom_point()`:

! Problem while computing aesthetics.

ℹ️ Error occurred in the 1st layer.

Caused by error:

! object 'EBITDA' not found

Run `rlang::last_trace()` to see where the error occurred.

> dit zegt de error

```r
names(filtered_datasetSummary)
```

```r
names(filtered_datasetSummary)
# [1] "BD" "DE" "log_EBITDA" "log_CurRatio" "log_MCap" "log_AcqNetDebt" "TotalValue"
```

```r
vars_to_plot <- c("BD", "DE", "log_EBITDA", "log_CurRatio", "log_MCap", "log_AcqNetDebt")
base_var <- "TotalValue"
```

```r
plots <- lapply(vars_to_plot, function(var) {
  ggplot(filtered_datasetSummary, aes_string(x = var, y = base_var)) +
    geom_point(alpha = 0.6, color = "steelblue") +
    geom_smooth(method = "lm", se = FALSE, color = "darkred", linetype = "dashed") +
    labs(
```

```
      title = paste(var, "vs", base_var),
      x = var,
      y = base_var
    ) +
    theme_minimal(base_size = 10)
})
```

Laat het me weten als je wilt dat ik de hele code opnieuw schrijf met de juiste kolomnamen uit jouw dataset!

ik krijg nu scatterplots tegen Total_Value, ik wil graag een scatterplot van de observaties zelf zien

```r
library(ggplot2)
library(patchwork)

# Kolommen die je wilt visualiseren
vars_to_plot <- c("BD", "DE", "EBITDA", "CurRatio", "MCap", "AcqNetDebt", "TotalValue")

# Zet een ID-index toe voor observaties
filtered_datasetSummary$Observation <- 1:nrow(filtered_datasetSummary)

# Maak scatterplots per variabele
plots <- lapply(vars_to_plot, function(var) {
  ggplot(filtered_datasetSummary, aes_string(x = "Observation", y = var)) +
    geom_point(color = "steelblue", alpha = 0.6) +
    geom_line(color = "grey70", alpha = 0.4) +
    labs(title = paste("Spreiding van", var), x = "Observatie", y = var) +
    theme_minimal(base_size = 10)
```

})

Combineer plots op 1 pagina (bijvoorbeeld 3 kolommen breed)

combined_plot <- wrap_plots(plots, ncol = 3)

Toon het plot

print(combined_plot)

dit is al erg mooi, zou je de schaal van DE, BD en TotalValue kunnen wijzigen zonder de schaal van de andere variabelen aan te passen? DE en BD zijn namelijk hele kleine getallen, TotalValue is een groot getal

```r
library(ggplot2)
library(patchwork)
library(officer)
library(magrittr)

# Variabelen en welke log-transformatie nodig hebben
vars <- c("BD", "DE", "TotalValue", "log_EBITDA", "CurRatio", "log_MCap", "AcqNetDebt")
log_scale_vars <- c("BD", "DE", "TotalValue")

# Check op ontbrekende variabelen
missing_vars <- setdiff(vars, names(filtered_datasetsummary))
if (length(missing_vars) > 0) {
  stop(paste("De volgende variabelen ontbreken in de dataset:", paste(missing_vars, collapse = ",
")))
}

# Maak de plots
```

```
plot_list <- lapply(vars, function(var) {
  p <- ggplot(filtered_datasetsummary, aes_string(x = seq_len(nrow(filtered_datasetsummary)),
y = var)) +
    geom_point(color = "#0072B2", alpha = 0.7) +
    theme_minimal() +
    labs(title = var, x = "Observatie", y = var)

  # Voeg log-schaal toe voor specifieke variabelen
  if (var %in% log_scale_vars) {
    p <- p + scale_y_log10()
  }

  return(p)
})

# Combineer de plots in een grid
combined_plot <- wrap_plots(plotlist = plot_list, ncol = 2)

# Sla figuur op als afbeelding
ggsave("scatter_combined_scaled.png", plot = combined_plot, width = 10, height = 8, dpi = 300)

# Exporteer naar Word
doc <- read_docx() %>%
  body_add_par("Spreidingsplots met geschaalde variabelen", style = "heading 1") %>%
  body_add_img(src = "scatter_combined_scaled.png", width = 6.5, height = 5.5)

# Bewaar het document
print(doc, target = "Spreidingsplots_Geschaald.docx")
```
```
```

Error in match(x, table, nomatch = 0L) :

'match' requires vector arguments, ik krijg deze error bij voeg schaal toe als gedefinieerd

```r
library(ggplot2)
library(patchwork)
library(officer)
library(magrittr)

# Variabelen en aangepaste limieten
vars <- c("BD", "DE", "TotalValue", "log_EBITDA", "CurRatio", "log_MCap", "AcqNetDebt")
custom_limits <- list(
  "BD" = c(-200, 150),
  "DE" = c(-2, 850),
  "TotalValue" = c(0, 3e6)
)

# Maak de scatterplots
plot_list <- lapply(vars, function(v) {
  # Start basisplot
  p <- ggplot(filtered_datasetsummary, aes(x = seq_along(filtered_datasetsummary[[v]]), y = filtered_datasetsummary[[v]])) +
    geom_point(color = "#0072B2", alpha = 0.7) +
    theme_minimal() +
    labs(title = v, x = "Observatie", y = v)

  # Pas y-as aan indien limiet bekend is
  if (!is.null(custom_limits[[v]])) {
```

```
    p <- p + scale_y_continuous(limits = custom_limits[[v]])
  }

  return(p)
})

# Combineer de plots
combined_plot <- wrap_plots(plotlist = plot_list, ncol = 2)

# Sla afbeelding op
ggsave("scatter_combined_rescaled.png", plot = combined_plot, width = 10, height = 8, dpi = 300)

# Voeg toe aan Word-document
doc <- read_docx() %>%
  body_add_par("Spreidingsplots met herschaalde assen", style = "heading 1") %>%
  body_add_img(src = "scatter_combined_rescaled.png", width = 6.5, height = 5.5)

# Bewaar het document
print(doc, target = "Spreidingsplots_Rescaled.docx")
```

Error: object 'v' not found, ik krijg nu deze foutcode

Die fout komt doordat binnen de `lapply()`-functie het argument `v` soms niet goed wordt herkend in het innerelement van `aes()` of ergens anders. Dat kan gebeuren als `v` niet wordt geëvalueerd in de juiste omgeving.

Je kunt dit voorkomen door **een `local()` of een anonieme functie te gebruiken die `v` 'vastlegt'** binnen de lus, of door direct `aes_string()` te gebruiken in plaats van `aes()`. `aes_string()` accepteert een string als variabele-naam, wat hier precies handig is.

Hier is de verbeterde versie van de code waarin ik `aes_string()` gebruik om die fout te voorkomen:

```r
library(ggplot2)
library(patchwork)
library(officer)
library(magrittr)

# Variabelen en aangepaste limieten
vars <- c("BD", "DE", "TotalValue", "log_EBITDA", "CurRatio", "log_MCap", "AcqNetDebt")
custom_limits <- list(
  "BD" = c(-200, 150),
  "DE" = c(-2, 850),
  "TotalValue" = c(0, 3e6)
)

# Maak de scatterplots
plot_list <- lapply(vars, function(v) {
  # basis plot met aes_string zodat v als string werkt
  p <- ggplot(filtered_datasetsummary, aes_string(x =
"seq_along(filtered_datasetsummary[[v]])", y = v)) +
    geom_point(color = "#0072B2", alpha = 0.7) +
    theme_minimal() +
    labs(title = v, x = "Observatie", y = v)

  # Pas y-as limiet aan als die er is
  if (!is.null(custom_limits[[v]])) {
```

```
    p <- p + scale_y_continuous(limits = custom_limits[[v]])
  }

  return(p)
})

# Combineer plots
combined_plot <- wrap_plots(plotlist = plot_list, ncol = 2)

# Sla afbeelding op
ggsave("scatter_combined_rescaled.png", plot = combined_plot, width = 10, height = 8, dpi = 300)

# Voeg toe aan Word-document
doc <- read_docx() %>%
  body_add_par("Spreidingsplots met herschaalde assen", style = "heading 1") %>%
  body_add_img(src = "scatter_combined_rescaled.png", width = 6.5, height = 5.5)

# Bewaar het document
print(doc, target = "Spreidingsplots_Rescaled.docx")
```

Let op:
De `x`-as in de scatterplot is `seq_along(filtered_datasetsummary[[v]])` — een vector van indices — en die gebruik ik nu ook binnen `aes_string()`. Soms kan dit lastig zijn met `aes_string()`. Mocht je hier alsnog problemen krijgen, kun je het beter buiten `aes_string()` definiëren:

```r
plot_list <- lapply(vars, function(v) {
```

```
  x_vals <- seq_along(filtered_datasetsummary[[v]])
  y_vals <- filtered_datasetsummary[[v]]
  p <- ggplot(data = data.frame(x = x_vals, y = y_vals), aes(x = x, y = y)) +
    geom_point(color = "#0072B2", alpha = 0.7) +
    theme_minimal() +
    labs(title = v, x = "Observatie", y = v)

  if (!is.null(custom_limits[[v]])) {
    p <- p + scale_y_continuous(limits = custom_limits[[v]])
  }

  return(p)
})
```

Dit is stabieler en voorkomt scope-problemen. Wil je dat ik deze versie voor je schrijf?

kun je 1 code schrijven om de variabelen log_MCap, CurRatio en WXSR in 1 plot te krijgen? op basis van de volgende code voor de robuuste bootstrap: boot_rlm <- function(data, indices) {

d <- data[indices,] # Bootstrap sample

model <- rlm(BD ~ log_MCap + CurRatio + WXSR, data = d)

return(coef(model)) # Geeft de coëfficiënten terug

}

 # Voer bootstrap uit (1000 herhalingen)

set.seed(123) # Voor reproduceerbaarheid

boot_results <- boot(data = dataset_log, statistic = boot_rlm, R = 10000)

 # Bekijk resultaten

```
print(boot_results)

# Percentiel betrouwbaarheidsintervallen (95%) voor alle coëfficiënten
for (i in 1:length(boot_results$t0)) {
  cat("\n95% CI voor:", names(boot_results$t0)[i], "\n")
  print(boot.ci(boot_results, type = "perc", index = i))
}

# Gemiddelden en percentiel-intervallen (95%)
boot_summary <- data.frame(
  Coefficient = names(boot_results$t0),
  Estimate = boot_results$t0,
  CI_lower = apply(boot_results$t, 2, function(x) quantile(x, 0.025)),
  CI_upper = apply(boot_results$t, 2, function(x) quantile(x, 0.975))
)

library(ggplot2)
library(dplyr)
library(tidyr)

# Zet bootstrapresultaten om naar dataframe
boot_df <- as.data.frame(boot_results$t)
colnames(boot_df) <- names(boot_results$t0)

# Selecteer variabelen
boot_selected <- boot_df %>%
  select(log_MCap, CurRatio, WXSR)

# Zet om naar long format
```

```
boot_long <- boot_selected %>%
  pivot_longer(everything(), names_to = "Variabele", values_to = "Schatting")

# Voeg originele (punt)schattingen toe
boot_long <- boot_long %>%
  mutate(Origineel = case_when(
    Variabele == "log_MCap" ~ boot_results$t0["log_MCap"],
    Variabele == "CurRatio" ~ boot_results$t0["CurRatio"],
    Variabele == "WXSR"     ~ boot_results$t0["WXSR"]
  ))

# Bereken per variabele de 2.5e en 97.5e percentiel voor x-as
x_limits <- boot_long %>%
  group_by(Variabele) %>%
  summarise(xmin = quantile(Schatting, 0.025),
            xmax = quantile(Schatting, 0.975))

# Plot met dynamische x-limieten via facetting + scales = "free"
ggplot(boot_long, aes(x = Schatting)) +
  geom_histogram(bins = 50, fill = "steelblue", color = "white", alpha = 0.8) +
  geom_vline(aes(xintercept = Origineel), color = "red", linetype = "dashed") +
  facet_wrap(~Variabele, scales = "free", ncol = 1) +
  labs(title = "Bootstrapverdelingen met focus op centrale waarden",
       x = "Bootstrap-schatting", y = "Frequentie") +
  theme_minimal(base_size = 13) +
  coord_cartesian(clip = "off") +  # zorgt dat as-aanpassing werkt
  facet_wrap(~Variabele, scales = "free", ncol = 1,
             labeller = label_value) +
  geom_blank(data = x_limits, aes(x = xmin)) +  # forceert linkergrens
```

```
  geom_blank(data = x_limits, aes(x = xmax))    # forceert rechtergrens
# Laad benodigde packages
library(ggplot2)
library(dplyr)
library(tidyr)
library(officer)
library(rvg)  # voor vectorkwaliteit in Word

# Stap 1: zet bootstrapresultaten om naar dataframe
boot_df <- as.data.frame(boot_results$t)
colnames(boot_df) <- names(boot_results$t0)

# Stap 2: selecteer relevante variabelen
boot_selected <- boot_df %>%
  select(log_MCap, CurRatio, WXSR)

# Stap 3: naar long format + originele schattingen toevoegen
boot_long <- boot_selected %>%
  pivot_longer(everything(), names_to = "Variabele", values_to = "Schatting") %>%
  mutate(Origineel = case_when(
    Variabele == "log_MCap" ~ boot_results$t0["log_MCap"],
    Variabele == "CurRatio" ~ boot_results$t0["CurRatio"],
    Variabele == "WXSR"     ~ boot_results$t0["WXSR"]
  ))

# Stap 4: plot maken (met facetten)
boot_plot <- ggplot(boot_long, aes(x = Schatting)) +
  geom_histogram(bins = 50, fill = "steelblue", color = "white", alpha = 0.8) +
  geom_vline(aes(xintercept = Origineel), color = "red", linetype = "dashed") +
```

```
  facet_wrap(~Variabele, scales = "free", ncol = 1) +
  labs(title = "Bootstrap-verdelingen (90% focus)",
       x = "Bootstrap-schatting", y = "Frequentie") +
  theme_minimal(base_size = 12)

# Stap 5: Word-document aanmaken en plot invoegen
doc <- read_docx() %>%
  body_add_par("Figuur: Bootstrap verdelingen van log_MCap, CurRatio en WXSR", style = "heading 1") %>%
  body_add_gg(value = boot_plot, width = 6.5, height = 8, style = "centered")

# Stap 6: Opslaan
print(doc, target = "Bootstrap_Plots.docx")
```

ik heb 2 kolommen in mijn dataset die een getal in de naam hebben, hoe verander ik deze, de rename command geeft namelijk een error code

```
library(dplyr)


dataset_log <- dataset_log %>%
  rename(
    EBITDA = `EBITDA_2023`,
    Revenue = `Revenue2022`
  )
```

geef een R script om een nieuwe kolom te maken in dataset_filtered, waarbij voor elke observatie de waarden in kolom DE wordt vermenigvuldigd met de waarden in kolom EBITDA

```
# Voeg nieuwe kolom toe waarin DE wordt vermenigvuldigd met EBITDA
dataset_filtered <- dataset_filtered %>%
  mutate(DE_x_EBITDA = DE * EBITDA)
```

Laat me weten als je wilt filteren op bepaalde voorwaarden of als je kolomnamen iets anders zijn.

geef mij een script om de 5 grootste waarden van de variabele BD uit de dataset dataset_bigBD te halen als robuustheidstest

```
# Stap 1: Rangschik op BD van hoog naar laag
dataset_bigBD_sorted <- dataset_bigBD %>%
  arrange(desc(BD))

# Stap 2: Verwijder de 5 grootste BD-observaties
dataset_bigBD_robust <- dataset_bigBD_sorted %>%
  slice(-(1:5))  # verwijder rijen 1 t/m 5 (de hoogste BD's)

# Optioneel: controleer of het werkt
head(dataset_bigBD_robust$BD)
```

how how do I arrange ascending?

```
library(dplyr)

dataset_bigBD_sorted <- dataset_bigBD %>%
  arrange(BD)  # ascending by default
```