The Issuance of German SME Bonds and its Impact on Operating Performance

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Abstract This article investigates the post-issuance performance of firms in the German SME Bond (Mittelstandsanleihen) market segment. In particular, we ask if issuers' operating performance is significantly different relative to an ex-ante indistinguishable non-issuer control sample. To properly identify the comparison sample and avoid endogeneity concerns, we implement a propensity score matching process based on a set of financial variables. Our main results show that issuers actually display lower post-issuance operating performance which amplifies their financial fragility. Our results contribute to the discussion if the poor performance of this market segment could have been identified ex-ante.

Keywords Post-Issuance Performance · German SME Bonds · Mittelstandsanleihen · Propensity Score

MSC-Classification JEL · G10 · G20 · G30

1 Introduction

The German SME bond market (also called mini-bonds) is a fixed-income segment created on several German exchanges around 2009–2010. The main novelty was the reduction in the minimum issuance volume from €100 million to (depending on

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the exchange) around €10 million together with lower standards regarding the investment prospectus. These factors allowed smaller firms to get access to an actively traded secondary market for public debt and the market segment was conceived favorably at its inception, mainly because it was seen as a post-crisis possibility for smaller firms to break their traditional reliance on the banking system to raise capital (Feiler and Kirstein 2014; Horsch and Ueberschär 2013). Given that SMEs are the backbone of the German economy and are frequently faced with financial constraints, the SME bond market was warmly welcomed and predicted a bright future. The segment saw a large increase in issuances for a few years before the first defaults appeared and issuance activity almost stopped completely in 2014 (Hasler 2014). As of this writing, around a third of all issuers were partially or completely unable to make coupon payments and/or to repay principal. The failure of this market segment has triggered an enormous amount of comments in the public press, but until now only a limited number of contributions in the academic literature. The likely reason is that anecdotal evidence suggests that the market suffered from few but prominent cases of corporate behaviour which appear as entrepreneurial hybris or even being close to fraudulent conduct. Cases which raise interest in the public media, but are less well-suited for empirical research based on financial fundamentals.

With this in mind, this article aims at contributing to the understanding of the market failure by restricting the focus to an analysis of economic fundamentals of issuing firms. In particular, we ask if and how the issuance of SME bonds had an impact on the operating performance of the issuing firm in the subsequent years. Such an analysis can contribute to the discussion if the – to put it mildly – less than advantageous development of the market could have been anticipated by market participants. Market participants such as exchanges, rating agencies, underwriters and investors were frequently blamed in the public media for being overly optimistic over the prospects of this market segment. The few research articles seem to partly confirm the claim by showing that credit spreads did not properly reflect the inherent risks (see for example Kinatader et al 2015 or Schöning 2014) or that initial ratings appear to have been overoptimistic (Mietzner et al 2015).

However, before drawing any firm conclusions, one should make sure not to succumb to the hindsight bias. Mietzner et al (2015) for example draw their conclusions from comparing initial ratings to realized default rates.¹ Ex post, it is evident that realized default rates are way higher than implied by initial ratings. However, it does not speak to the question to what extent it could have been anticipated ex-ante, given the lack of experience with SME bond issuers. Thus, we consider it to be a crucial step in the analysis to determine a proper comparison sample against which performance of an issuing firm can be evaluated. In more abstract terms, any analysis of SME bond issuers has to deal with a potential endogeneity concern that may lead to a systematic selection bias of firms deciding to engage in this market segment. Our methodical approach to address this issue is to implement a novel variant of propensity score matching. Propensity score matching highlight the “comparability” of issuers and non-issuers and is also a good choice for situations like ours with rel-

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¹ They also compare to a simple credit risk model. By construction, this is a test to what extent a model captures actual ratings.

atively small sample sizes. In essence, we emulate a random controlled experiment by setting up two groups, issuers and non-issuers, which were, prior to the issue, identical (or at least as similar as possible) and analyze differences between them after the issue.

In order to be able to set up a control sample which is as similar as possible to the treatment sample, it is important to have an extensive database to draw from. With this respect our article is distinct from the existing literature by having access to the Creditreform database, a proprietary collection of more than one million German firms' financial reports. While the underlying financial reports are mostly publicly available (with the exception of certain legal forms), the data is digitally processed and sorted by Creditreform, a financial services provider headquartered in Germany. With this data, we can focus on the change (or lack thereof) in key financial reporting figures after the issuance and how this relates to the development among non-issuers. To the best of our knowledge, no other study currently analyzes the German SME bond market on the firm-level with such in-depth financial statement information.

We find, based on our comparison of post-issue performance of issuers and non-issuers a significant deterioration in issuers' Profit/Loss (P/L) figures after the issuance. Given the generally poor performance in the SME bond market, this finding may be unsurprising. However, a further analysis shows that even though interest expenses are significantly higher due to the issuances, importantly, we detect a general decline in proxies for the economic performance such as total profitability, EBIT & cash flows. So, besides increased financial risk, we document that the issuance of SME bonds is also accompanied by a significant drop in subsequent operating performance. Our general results are robust to differing specifications of the propensity score model and an OLS regression analysis. Our findings have implications for the discussion to what extent the poor performance of the mini bond market could have been foreseeable. By putting the emphasis on constructing a comparison sample which is *ex ante* (statistically) indistinguishable but shows different results *ex post*, it can be concluded that the development was not identifiable from the *ex ante* information set. Since our information set consists of comprehensive financial variables, we can conclude that a substantial part of the comparatively poor development in operating performance of issuing companies was apparently not predictable from the financial information before the issuance.²

In light of the initial euphoria about the German SME bond market, our results may contribute to the broader discussion if it is in general a good idea to establish new market segments for companies with little capital market experience. Although this question touches on many more aspects than those we have addressed in our empirical analysis, our results are rather discouraging for similar future initiatives.

This article is structured as follows: Because there is no shortage of arguments and hypotheses in mainstream and financial media why this German SME bond market failed, we discuss in Sect. 2 existing literature that deals specifically with this segment and also the more general research on the effects of security issuance (e.g. debt, equity, etc) on issuers. In Sect. 3, our propensity score matching approach

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² As noted above, we only focus on financial fundamentals. If poor performance due to entrepreneurial hubris or outright fraud was foreseeable is a question beyond our scope.

is explained in rigorous detail to provide the reader with a basic understanding of this, in finance, little used method. In Sect. 4, the SME bond market's emission frequency and market environment is presented as well as our dataset and details on the implementation of the propensity score matching. Sect. 5 then presents the main results of our study in Sect. 5.1 before sensitivity and robustness checks are shown in Sect. 5.3. Sect. 6 concludes.

2 Related Literature

From an efficient markets perspective, the potential defaults should have been anticipated as possibilities by investors, who should have required a higher risk premium, e.g. Schöning (2014) showed, using a credit model, that the risk-adjusted returns of the bonds were not high enough. Heß and Ueber (2013) found that, contrary to nearly all other developed fixed-income markets, over half of issuers failed to reach their target issue volume. They also find that financial health, use of issue funds, timing and investor relations had been important determinants of issue success, which was measured by the percentage of target volume actually raised. Kinader et al (2015) studied credit spreads and their characteristics in both SME and large issuer bonds. They came to the conclusion that the German SME bond market was treated (as evidenced by credit spreads) quite differently by investors, indicating low overall integration of the market. This implies high idiosyncratic risks. Mietzner et al (2015) stated that there had been an apparent inflation of high-quality ratings issued by ratings agencies, a finding based on a comparison of ratings to a credit risk model. Therefore, low-quality firms had been able to enter the market in relatively high proportions and the authors found that high-quality firms had signaled their quality with higher underpricings.

On the one hand, these studies indicate that too many firms of low quality were able to finance themselves cheaply in the German SME bond market. Relatedly, there were apparent problems by many financial market participants, including rating agencies and investors, to make correct assessments of the true value and risk of these securities. On the other hand, none of the studies, to the best of our knowledge, did take the actual development of the issuing firms, as measured by financial statements, after the issuance into account nor did they compare issuers to comparable non-issuers. In this context, the contribution of our work can be seen as the following: By looking at the financial statement data pre- and post-issuance, we can find out whether any pre-issue evaluation from investors, such as ratings for example, were inflated or not and whether issuing firms were truly of low quality. After the fact, it is easy to state (like in Mietzner et al (2015)) that ratings have been overly positive when a segment disappoints like the German SME bond market, but what if issuing firms have been solid *before* the issuance? This is also related to the apparent mispricing found in Schöning (2014). Without hindsight bias, it is equally plausible that the pricings were correct and the defaults very improbable *ex-ante*.

Our work is also related to the more general literature on post-debt-issuance performance beyond the scope of German SME bond markets. There is a large body of empirical studies evaluating post-issuance performances of security issuers.

Contributions focusing on debt are, however, not as prevalent as those focusing on equity. One of the few works dealing with debt, Dichev and Piotroski (1999), found that public debt issuers, underperform³ their peers for five years after the issue. In Hansen and Crutchley (1990), the authors reported a financing year downturn in earnings, concluding that firms issue debt to survive bad years. McLaughlin et al (1998) as well as Bae et al (2002) showed that all types (e.g. equity, convertibles, debt, etc.) of security issuers have strong operating performances prior to issuing and declining performances after the issues, with the difference being larger for equity than for debt. Patel et al (1993) on the other hand find that debt issuers do not suffer from post-issue declines in performance (but report similar results for equity issuers). Specifically having focused on high-yield bonds (as the majority of bonds in our sample could be classified), Wolfe (2009) concluded that high-yield issuers suffer more from underperformance than their high-quality counterparts. Analogically, Spiess and Affleck-Graves (1999), besides having confirmed the basic negative effect of security issues, found that smaller, younger firms with bad or no ratings are more likely to underperform. Evidence from pure equity issues, as presented in Ritter (1991) or Jain and Kini (1994) for example, showed also negative effects of securities issues. This stream of literature is also relevant for our sample, especially from a pecking order theory standpoint.⁴

Overall, the literature on debt issuances showed that issuances have a detrimental effect on firms. This is relevant for the German SME bond market as the majority of the firms/issuances fit the criteria (small size, low credit ratings, high coupons, etc.) identified as those who are associated to a stronger decline in performance.

Our research approach, by focusing on financial statement data in a propensity score method, should yield valuable insights whether firms were, as the recent literature on German SME bonds suggests, unfit to enter the market or if the issuance itself is associated with the operating downturns, as the general literature on debt issuances implies.

3 Propensity Score Matching

To analyze the operating development of issuers *after* and *because* of the issuance, we are using optimal propensity score matching with subsequent simple evaluations

³ The study uses stock returns to assess the impact of debt issuance. Even though stock returns are not observable for the majority of firms in our sample, note that Bae et al (2002) show that operating performance and stock performance behave qualitatively similar for these types of analyses.

⁴ For example, López-Gracia and Sogorb-Mira (2008) found that (Spanish) SMEs behave like predicted by the pecking order theory, which is based on the work by Myers and Majluf (1984). The theory states that there is no target capital structure towards which firms converge. Instead, firms simply use those funds which associated with the lowest costs, after informational asymmetry costs. This implies that firms should prefer internal funds to debt and debt to equity. For regular firms, public equity is the financing instrument with the highest associated asymmetric information, however for many of the German SME firms in our sample, public equity is not an option due to the lack of size and the magnitude of fixed issuance costs. So, one could argue that for them, the pecking order only includes retained earnings, private and public debt. There are, of course, many alternative rationales behind capital structure choice, like Ross (1977), Harris and Raviv (1990) or Heinkel (1982).

of differences in several P/L figures after the issuance. The basic idea is to emulate a controlled experiment by matching issuers (treated) and non-issuers (untreated) which are indistinguishable *ex-ante* with respect to X . Then, we can attribute *ex-post* differences in Y to the treatment, in our case the issuance of bonds.⁵

In our empirical setting, we observe for all firms the binary vector T , indicating issuance. Furthermore, we can observe X , a matrix consisting of several financial statement variables, measured before the issuance. The outcome variable matrix Y is also available and consists in our case of several P/L figures. Denote with Y_{1i} and Y_{0i} as the outcomes of a firm i after the issuance and non-issuance of bonds respectively. Naturally, the simultaneous measurement is impossible and therefore Y_{0i} is proxied via a pseudo-treated entity j , which is, pre-issue, “similar” to i across X .

The metric for “similarity” is the firms’ *probability of issuance* given X . In the terms of the original paper by Rosenbaum and Rubin (1983), this is called the *true* propensity score $P_i(X) = \text{Prob}(T_i = 1 \mid X_i)$, which we estimate for a firm i given its set of financial reporting variables X_i . A propensity score model is properly specified if the unconfoundedness assumption

$$(Y_0, Y_1) \perp T \mid P(X) \quad (1)$$

holds together with the condition that there is a chance to be an issuer *and* a non-issuer at every level of $P(X)$:

$$0 < \text{Prob}(T = 1 \mid P(X)) < 1. \quad (2)$$

Thus, Y is unbiased with respect to T . The propensity score balances the distribution of X and therefore, conditioning the sample on a well-specified $\hat{P}(X)$ ensures unbiased estimation of issuance effects. Problems from self-selection into issuance, e.g. T causally depending on X , are reduced.⁶

X needs to contain all covariates that correlate with the bond issuance decision (T) as well as correlate with the P/L figures in Y (Luellen et al 2005). We use the pragmatic approach described in Steiner et al (2010) and identify the economically most important variables for bond issuance and P/L figures. Our approach intends to reflect the perspective of a rating agency or investor who wishes to evaluate the firms *ex-ante* based on financial statement variables. A more detailed discussion about our specific covariate selection is given in Sect. 4.3.⁷

⁵ For a further discussion on the advantages of propensity score methods over more conventional approaches, we forward the reader to Rosenbaum (1989), Zhong (2008), (Heckman et al 1998b), (Dehejia and Wahba 2002), Li (2013), Austin (2011a), Luellen et al (2005) and others. For the scope of this paper, it is sufficient to mention that we chose propensity score methods due to their explicit focus on creating comparable groups for analysis, solving extrapolation and self-selections problems. They rely little on parametrizations, distributional assumptions and are conceptually and computationally simple.

⁶ Further details can be found in the seminal work by Rosenbaum and Rubin (1983) and/or the citations in the following subsections.

⁷ For more general discussion on covariate selection, refer to Rubin and Thomas (1996).

We implement, instead of the widely used logit/probit models, a boosted regression tree model to estimate $\hat{P}(X)$. This method is described in McCaffrey et al (2004) or Elith et al (2008) and allows modeling of $Prob(T = 1)$ given T and X . Boosted regression trees automatically identify and weight important and less important predictors without distributional assumptions and are therefore more robust when it comes to sample selection. They belong to machine learning algorithms and are basically an adaptive and iterative way to combine multiple regression trees, fitted to random subsamples of the data at each iteration (Elith et al 2008). Their strength is adapting to a multitude of non-linear and joint relationships. Their only downside, the so-called “black-box” problem is of minor concern in propensity score models since balance (see below) is required, whereas the model itself to reach balance is of lesser concern (D’Agostino 1998).

The forecasted values of this boosted regression tree model for each firm are our estimated propensity scores $\hat{P}(X)$. As a conditioning method, we choose optimal 1:3 matching on propensity scores, so every issuer i receives up to three non-issuers (based on an algorithm which minimizes total distance in $\hat{P}(X_i)$ across all pairs). Their average Y is then used to proxy Y_{0i} .

From some threshold of dissimilarity onwards, an issuer should not be assigned a non-issuer. Thus, a so-called “caliper” φ (see for example Rubin and Thomas 1996) is introduced. An issuer firm i and a non-issuer firm j are only seen as similar if $|\hat{P}(X_i) - \hat{P}(X_j)| < \varphi$ holds. For the caliper-width, we choose the value proposed by Austin (2011b) of

$$\varphi = 0.2 \times \hat{s} \left(\log \left(\frac{\hat{P}(X)}{1 - \hat{P}(X)} \right) \right), \quad (3)$$

with $\hat{s}$ being the sample standard deviation and the term in brackets being the logit of estimated propensity scores. This dynamic caliper adapts to the distribution of $\hat{P}(X)$ itself. An issuer with less than three non-issuers within φ distance receives less than three or no matches at all.⁸

The common support, intuitively described as the multidimensional overlap in X between issuer and non-issuers is a very important concept in propensity score studies (Ho et al 2007; Lechner 2008). It is violated when the probability of observing a pseudo-issuer is zero (see Eq. 2) for a given set of X , e.g. a realization of X where it is *impossible to not* issue bonds.

We base our innovative way to ensure common support on King and Zeng (2006). In contrast to most prior works, we evaluate common support *before* the estimation of $\hat{P}(X)$ directly on X and only retain a non-issuer firm if it fulfills at least one of the following three conditions: First, it has to be inside the convex hull of $X \mid T = 1$. Second, the firm has to be close to the multidimensional center of $X \mid T = 1$ as measured by the Mahalanobis distance. Third, the firm has to be, in the multidimensional space of X , near a cluster of issuer firms as measured by

⁸ Ming and Rosenbaum (2001) provide details on the exact algorithm to perform optimal matching like it is implemented in our work.

Table 1 Variables in X for Estimation of $\hat{P}(X)$ and Outcome Variables Y

X	Description	Calculated As
AST	Asset Tangibility	$\frac{\text{Fixed Assets}}{\text{Total Assets}}$
LEV	Leverage	$\frac{\text{Equity}}{\text{Debt}}$
LIQ	Liquidity	$\frac{\text{Current Assets}}{\text{Short-Term Debt}}$
TPR	Total Profitability	$\frac{\text{Net Income} + \text{Interest}}{\text{Total Assets}}$
SIZ	Size	$\log(\text{Total Assets} - \text{Intangibles})$
SOL	Solvency	$\frac{\text{EBIT}}{\text{Interest}}$
STO	Sales Turnover	$\frac{\text{Sales}}{\text{Total Assets}}$
Y	Description	Calculated As
TPR	Total Profitability	$\frac{\text{Net Income} + \text{Interest}}{\text{Total Assets}}$
ROA	Return on Assets	$\frac{\text{Net Income}}{\text{Total Assets}}$
STO	Sales Turnover	$\frac{\text{Sales}}{\text{Total Assets}}$
OPM	Operating Profit Margin	$\frac{\text{EBIT}}{\text{Sales}}$
INT	Inverse Interest Coverage	$\frac{\text{Interest}}{\text{EBIT}}$
TXE	Taxes and Extraordinary Items	$\frac{\text{Taxes \& Extraordinary}}{\text{EBT}}$

the Gower distance to a fraction of issuers.⁹ Qualitatively, these criteria ensure that a non-issuer firm is only used for our analysis if it does not require extrapolation or it is close to the average issuer or it is close to a sizeable subset of issuers.

Balancing checks assess whether Eq. 1 holds. After $\hat{P}(X)$ was estimated for the common support of X and issuers were matched to non-issuers based on $\hat{P}(X)$ to form matched issuer/non-issuer samples, this vital step now analyzes the differences in the distributions of X for these matched issuer and non-issuer samples (see, among others, Ho et al (2007)). If matching was successful, no or only negligible differences remain. Most papers focus only on a select few types of checks but we will report summary statistics, quartiles, higher moments, various statistical test results and visualizations to evaluate balance from multiple perspectives.¹⁰

⁹ We developed this novel method given the concerns about $\hat{P}(X)$ -based common support evaluation mentioned in King and Zeng (2006) and King and Zeng (2007) and it translates the intuition behind widely used single-dimensional common support checks on $\hat{P}(X)$ to the multidimensional case of X (see for example Caliendo and Kopeinig (2008), Becker and Ichino (2002) and Smith and Todd (2005) respectively for methods that mirror our three criteria in the single-dimensional case of $\hat{P}(X)$).

¹⁰ The open question on if and how balance can be proven and demonstrated is dealt with, among other balance-related topics, for example in Austin (2009) and Imai et al (2008).

If we observe satisfactory balance, we can finally estimate the impact of bond issuance on the issuers. In our case, we compare the issuers' Y (see lower panel in Table 1) in the issuance and post-issuance year relative to the matched non-issuer firms. Following Imai et al (2008) and Austin (2011a), we carry out t -tests and Wilcoxon tests regarding the differences in means and medians. We also report the results of tests regarding variance and distributional differences.

4 The German SME Bond Market, Data and Matching Process

This section gives a short overview over our data source, provides summary statistics and also introduces the reader briefly into the German SME bond market.

4.1 German SME Bond Market and Environment

Looking at the issuance frequency in Fig. 1 shows how the market segment boomed in 2011 and 2012 with almost 40 issues annually. The biggest activity occurred in 2013, when firms issued nearly 50 bonds in the German SME segments. A relatively sharp downtrend in 2014 saw only 30 new bonds on the exchanges, setting a trend for the following years. We see a seasonality effect as the markets were less active during months at the beginning and middle of the respective years compared to the second and fourth quarters. Fig. 2 presents background information on the bond market environment. We can see that these factors underwent a significant shift over the first months of 2011. Before 2011, real interest rates were low but still positive. After 2011, they went down to and below 0. Credit spreads also changed at the same time and stayed on a level around twice as high as before. Term spreads declined relatively consistently over the whole period from 2010 to 2014.

From the perspective of a bond issuer, interest rates trended down, which is good, but only for high-quality issuers. Less credit-worthy corporate issuers had to pay, starting from middle to late 2011, significantly more above comparable German Bunds. The flattening yield curve indicates that the overall economic outlook was perceived to be less than favorable. For investors, it was a tough period with non-existent returns on risk-free securities and growing economic uncertainties.

From Figs. 1 and 2, it is easy to see that the German SME bond market segment was able to attract many issuers and therefore investors. It is also evident that the market conditions changed quite significantly right around the time (early 2011) we observed the first real surge in issuances.

4.2 Data

We have year-end financial statement data from Creditreform from between 2008 and 2014. The Creditreform AG provides us with access to financial statement data of over 1,000,000 German firms, the proprietary "Creditreform Bilanzdatenbank" which is based on (for the most part) publicly available financial reports, as mandated by German law. Using (in principal, publicly available) year-end financial data, the firm utilizes a specifically designed procedure to collect, structure and dig-

Fig. 1 German SME Bond Market Issuance Activity. This Figure shows two monthly time series from the beginning of 2010 to the end of 2014. “SME Issuance frequency” is simply the absolute number of issuances on German SME exchange segments in the respective month and “Quarterly Average” refers to the average of issuances in absolute terms of the three-month period up until and including the current month

Fig. 2 Bond Market Environment. This Figure shows three monthly time series from the beginning of 2010 to the end of 2014. The “Real Interest Rate” time series is arrived at by subtracting the change in the German consumer price index from the yield on two-year German bunds. “Term Spread” is calculated as the difference between the yield on seven-year and two-year German bunds and “Credit Spread” is defined as the difference of the yield on a German investment grade corporate bond fund and the yield on seven year German bunds

italise financial statement information. Each firm can be identified through a unique Creditreform-ID and for most firms we do not have only balance sheet, P/L and cash flow data but also firm address, founding date, legal form, number of employees, information regarding ownership/shareholder structure and sector membership.

We have 55 issuers for which we have three years with complete data, so that X is available for years t_{-1}, t_0, t_1 , with t_0 being the year of issuance. Even though well over 100 firms issued bonds on the German SME bond markets, the delay in reporting financial statements and incomplete inclusion into the database limits our

issuer sample. Using the three years of data, we can match firms on the t_{-1} year and subsequently analyze outcome variable differences in years t_0 and t_1 . The 55 issuers entered the market between 2011 and 2013 and they make up the total treatment group.

In Sect. 5.3, we conduct a test, where we account for the trend in the matching variables by additionally including t_{-2} data. For that robustness check, by avoiding the sector control due to providing another angle and due to sample size concerns, we have 59 issuers with enough data.

Regarding non-issuers, we possess a random sample of 10,000 German firms from the Creditreform data set. These firms do not have a “ t_0 ” as they never issued bonds. To counter survivorship biases, we only require that the non-issuers have three complete years of data, which is the same restriction as for issuers. The large volume and random nature of the non-issuer sample should alleviate sample imbalance errors described in Imai et al (2008): there is little reason to assume systematic biases in unobserved covariates between the population of issuers between 2011 and 2013 and a random sample of non-issuers. The large pool of non-issuers also increases the chance to find a comparable entity to match to each issuer.

4.3 Propensity Score Matching Process

As mentioned before (Sect. 3), the variable selection should ensure that issuers and non-issuers can be matched along observable covariates which correlate with both T and Y . In our case, we use variables that influence the decision to issue bonds and which relate to P/L numbers. The seven variables (upper panel in Table 1) contain the majority of information available as nearly all other variables in a financial report are basically linear combinations of them (e.g. current assets, interest, net profit margin, etc.) or otherwise correlated to more important variables (e.g. number of employees vs. total assets for size proxies). Over the next paragraphs, we will explain how the variables in X relate to T and Y . These relationships are only examples, not exhaustive and the actual relationship does not have to be linear or even monotonically increasing/decreasing.

AST is defined as the proportion of fixed assets the firm has. A firm with a low fixed asset base might seek to adjust this value to the sector-average by making large investments in fixed assets like machines or trucks. The relationship to the P/L statement is for example that AST serves as a proxy for the amount of capital tied up long-term, which also requires long-term financing and this naturally influences interest expenses. It is also a sector proxy even though we, as mentioned later in this section, control explicitly for sector membership, which has direct implications for operating (and total) margins for example.

LEV shows the ratio of equity and debt. A firm with high levels of debt might issue bonds in a favorable market environment to redeem older, more expensive debt. Similarly, a firm with a suboptimal level of leverage could choose to increase it by issuing debt and thus lower its cost of capital. LEV influences the P/L statement because interest payments are larger when a firm has more debt and it needs higher retained earnings to satisfy shareholders if it has more equity.

LIQ looks at the ratio of short-term assets versus short-term debt. A firm with low *LIQ* could issue bonds to acquire liquid assets in order to pay back short-term debt or to hold it in cash as a buffer. It relates to the P/L statement because of how short-term debt levels influence interest payments and because many current assets (cash, receivables, etc.) are related to EBIT.

TPR measures the distributable income scaled by size. Profitable firms could try to expand with fresh bond capital whereas less profitable firms could face problems raising external debt. Net income and interest are central figures of every P/L statement and thus influence all other P/L figures.

SIZ relates to the decision to issue bonds because larger firms can access financial markets easier in general. This is mostly due to the fixed costs of an issuance being distributed over a larger base. In relation to P/L statements, *SIZ* influences economies of scale which is related to sales and costs for example.

SOL is the ratio of EBIT and interest payments. A firm with low EBIT could try to invest in sales-generating or cost-cutting projects with the money from a bond issuance. Similarly, high interest payments could be reduced if the payments on the bonds are smaller than on existing debt. EBIT and interest payments are important figures of the P/L statement and the relationship to P/L is therefore straight-forward.

STO quantifies how efficient a firm is in generating sales per unit of size, measured as total assets. It relates to the decision to issue bonds because a less efficient firm could invest in additional machines, a new plant or try to expand in another country or business sector with the money generated from a bond issue. Sales is the first part of a P/L statement, from which all other P/L figures are either subtracted or to which they are added and is therefore a base for all other following P/L figures and it is also a sector and firm structure proxy due to the differing ability to create sales and the differing asset bases needed.

It is important to note that, even though they do not enter the propensity score model, we explicitly control for sector membership and year-effects by restricting matched firms to operate in the same industry (as measured by the German WZ classification system) and we also require the matched rows of financial data to come from the same year. So a firm issuing a bond in 2011, as mentioned before, will be matched on its t_{-1} -year, 2010, and the corresponding match can only come from non-issuer data from that year as long as that data belongs to a firm from the same industry. Both controls together will ensure that neither macro-trends in economic development nor micro-trends on a branch level skew the results. The sector control is especially helpful as it can proxy various qualitative aspects of a company.

For the outcome variables (lower panel in Table 1), we use multiple P/L figures to get a complete overview over how P/L statements change after the issue. For example, *TPR* could go down strongly, but this can be rooted in a reduction in sales as much as it could be caused by an increase in costs or a decrease in interest payments. To analyze the distributable income, we report *ROA* and *TPR* separately. The former is what remains for distribution to shareholders only whereas the latter represents all distributions, to debtholders and equityholders. As we analyze a debt financing event, *TPR* has the advantage to capture the fact that distributable income would mechanically shift, at least in part, from equityholders to debtholders when

increasing leverage, without an associated decrease in performance. Looking at *ROA* in addition to that provides further insight how equityholders were affected by the issuance. Note that total profitability (*TPR*) and sales over total assets (*STO*) are included in the propensity score model and in the outcome model. Imbens (2004) explicitly mentions that a lagged outcome can be included in the model of $\hat{P}(X)$ and this is equivalent to including a lagged dependent variable in a regression model among the independent variables. So, the firms are matched on the respective values in the pre-issue year and the outcome is analyzed across the two following years.

Regarding common support, we combine the intuition behind outlier detection mentioned in Sect. 3. After performing all three steps, every non-issuer firm that does not fulfil at least one of the criteria (or equivalently which is marked three times as an outlier) is removed. In total, 1.264 firms are outside the convex hull, 1.004 non-issuers are far away from the average treated entity and 1.319 non-issuers do not have a cluster containing at least 10 % of all issuers nearby. 819 firms are outliers in all three aspects and those are subsequently discarded from the analysis prior to estimating $\hat{P}(X)$.

Subsequently, as outlined in Sect. 3, the boosted regression tree model estimates the propensity scores for all 58 issuers and the remaining 346 non-issuers in the sample. Following Elith et al (2008), our parameters for the model are found via minimizing the mean squared error of the predictions. As we check for balance later on, the parameters are chosen in an iterative approach.

For the final model¹¹ that relates X to T , we show in Table 2 the relative importances of the variables in X with respect to explaining T . Due to the multitude of non-linear and joint effects considered by the model, we cannot say whether a variable has a positive or negative (or even a monotonic) relationship to T . We find that *LIQ*, *LEV*, *TPR* and *SOL* are the most influential variables for the decision to issue SME bonds. *SIZ* has average influence and unsurprisingly, *STO* and *AST* only have little impact on the bond decision to issue bonds when compared to the other variables.

Then, as described in Sect. 3, we matched all n issuers to m non-issuers with each issuer receiving at least $\alpha = 1$ and at most $\beta = 3$ non-issuers. The caliper width was dynamic to ensure it is related to the distribution of $\hat{P}(X)$, so all distances in the assignment problem matrix above this value were set to infinity, disallowing matches. In addition to controlling for the variables in X , we, as mentioned in Sect. 4.3, require matches to be exact on industry and on calendar year. Three issuers received only two matches and all others received the maximum of three matches. So the final matched sample for the analysis consists of 55 issuers and 169 non-issuers. To see whether we have truly build a counterfactual sample of controls which could be seen as “quasi-issuers”, e.g. those who shared all financial statement characteristics with issuers but ultimately did not issue, we perform balancing tests

¹¹ For comparability with other works: we chose a learning rate of 0.1, a minimum number of leafs in the trees of a 100th of the sample size and used 4 weak learners, e.g. regression trees while resampling 50 % of the sample at each iteration. We also cross-validated the sample with 10 folds, so that iteratively, a subsample comprising 9 of 10 parts of the sample is used to estimate the model, which is tested on the 10th part.

Table 2 Predictor Importances of X . This table shows the relative importances of the predictor variables of X as they relate to T in the boosted regression tree model for estimating $\hat{P}(X)$. This is calculated by scaling the mean squared errors of the individual tree splits by the mean squared errors of its subsequent tree splits. The higher the value, the higher the influence of the variables in the model. The columns refer to the variables used for estimating $\hat{P}(X)$ as described in Table 1. The values are given in units of 10×-3 for presentational purposes since the focus is on the relative importances between the variables and not on their absolute values

	<i>SIZ</i>	<i>LIQ</i>	<i>LEV</i>	<i>SOL</i>	<i>TPR</i>	<i>STO</i>	<i>AST</i>
Predictor Importance	1.208	2.478	2.178	1.839	1.904	0.489	0.320

and provide graphical and statistical comparisons of the two samples to see whether their distributions are the same.

In Table 3, we provide the most important descriptives for assessing balance (see Sect. 3), e.g. comparing issuers and non-issuers before and after matching. In the upper panel, the matched sample of issuers is compared to the matched sample of non-issuers. In the lower panel, the same statistics are shown for the total, unmatched samples. Table 4 shows the corresponding statistical tests regarding the differences. This analysis intends to show whether matching was successful. It is desired that the differences between the matched samples are as small as possible. While some measures are surprisingly similar for the total, unmatched sample, a closer look at the different moments and percentiles shows that matching resulted in two samples which are a lot more comparable than the simple total datasets for issuers and non-issuers. The statistical tests show a similar picture. While balance is not perfectly attained, we find a strong improvement in balance, as indicated by the relative lack of significances in the upper panel. The standardized differences show the differences in means between the issuers and non-issuers divided by a pooled variance. We also see an improvement of balance in this measure as the overall differences become smaller. Given the concerns about the validity of statistical tests in the context of assessing balance mentioned in Sect. 3, we use a graphical comparison in Fig. 3 between the total (panel a) and the matched samples (panel b). We see a tendency of the distribution to become less extreme and more similar overall. To summarize, after matching, no individual variable in X can be shown to be *clearly* different across location, dispersion and distribution. For the unmatched total samples however, one can make a strong case that at least four of the seven variables have differing distributions and moments.

Matching was successful if there remain no real differences between the two samples across X as analyzed via descriptives, statistical tests and visualizations. Across all variables, the matching process increased the balance. Certain outliers will remain outliers (influencing location, dispersion and distribution measures) and cannot be matched in all dimensions, but the vast majority of distributions seem to overlap quite favorably, which is underscored, as mentioned, by the negative test on distributional differences. So therefore we assume that Eq. 1 holds with a reasonable amount of certainty and we can continue with the analysis of the matched sample.

Table 3 Balancing: Descriptives Comparison. This table shows, in the upper panel, balancing descriptives for the matched issuer and non-issuer samples, whereas the bottom panel compares the total unmatched issuers and non-issuers. The issuer sample contains all issuers ($n = 55$) for whom at least one match was available in the matching comparison and all issuers otherwise. The non-issuer sample contains all control matches ($m = 169$) assigned to issuer units in the matching comparison and all non-issuers otherwise. The columns refer to the variables used for estimating $P(X)$ as described in Table 1.

Descriptive	Sample	SIZ_{t-1}	LIQ_{t-1}	LEV_{t-1}	SOL_{t-1}	TPR_{t-1}	STO_{t-1}	AST_{t-1}
Mean	Issuer Matched	18.16	148.37	0.42	24.74	7.34	1.52	37.39
	Non-Issuer Matched	17.67	138.53	0.48	23.18	7.04	1.60	37.52
Std. Dev.	Issuer Matched	1.11	88.11	0.60	142.91	6.97	1.00	24.10
	Non-Issuer Matched	0.83	41.69	0.28	56.92	3.17	0.61	17.70
Skewness	Issuer Matched	-0.01	2.01	4.18	7.22	1.36	0.36	0.30
	Non-Issuer Matched	0.37	0.46	0.80	4.78	0.45	0.62	0.61
Kurtosis	Issuer Matched	2.62	7.50	23.67	53.97	6.20	2.33	2.50
	Non-Issuer Matched	2.47	3.56	2.47	26.79	3.07	4.24	3.30
Minimum	Issuer Matched	15.42	38.74	0.01	-1.78	-7.74	0.11	0.97
	Non-Issuer Matched	16.10	39.59	0.02	-0.10	0.95	0.38	6.03
Lower Quartile	Issuer Matched	17.42	97.80	0.14	1.35	4.00	0.63	19.17
	Non-Issuer Matched	17.01	106.26	0.28	2.79	4.68	1.14	25.21
Median	Issuer Matched	18.15	126.34	0.32	2.12	6.29	1.37	39.01
	Non-Issuer Matched	17.54	137.77	0.39	5.91	7.09	1.58	35.73
Upper Quartile	Issuer Matched	18.90	168.84	0.48	5.03	8.73	2.39	50.50
	Non-Issuer Matched	18.22	163.30	0.60	18.51	9.37	2.01	47.43
Maximum	Issuer Matched	20.47	479.95	3.95	1084.39	30.74	3.85	91.96
	Non-Issuer Matched	19.74	259.59	1.09	364.35	16.78	3.71	87.21

Table 3 Balancing: Descriptives Comparison. This table shows, in the upper panel, balancing descriptives for the matched issuer and non-issuer samples, whereas the bottom panel compares the total unmatched issuers and non-issuers. The issuer sample contains all issuers ($n = 55$) for whom at least one match was available in the matching comparison and all issuers otherwise. The non-issuer sample contains all control matches ($m = 169$) assigned to issuer units in the matching comparison and all non-issuers otherwise. The columns refer to the variables used for estimating $P(X)$ as described in Table 1. (Continued)

Descriptive	Sample	SIZ_{t-1}	LIQ_{t-1}	LEV_{t-1}	SOL_{t-1}	TPR_{t-1}	STO_{t-1}	AST_{t-1}
Mean	Issuer Total	18.34	152.47	0.40	5.86	6.88	1.47	37.75
	Non-Issuer Total	16.97	149.39	1.09	-2564.60	7.22	2.06	40.93
Std. Dev.	Issuer Total	1.35	125.39	0.58	19.02	9.14	1.00	23.85
	Non-Issuer Total	1.50	90.96	2.90	52256.46	9.38	1.85	28.96
Skewness	Issuer Total	0.72	4.27	4.29	6.97	-0.92	0.40	0.29
	Non-Issuer Total	0.59	1.61	12.79	-18.04	-0.50	2.97	0.44
Kurtosis	Issuer Total	3.84	25.69	24.98	52.24	13.50	2.38	2.52
	Non-Issuer Total	4.46	6.14	199.88	328.58	10.99	18.15	1.99
Minimum	Issuer Total	15.42	38.74	0.00	-1.78	-38.33	0.01	0.15
	Non-Issuer Total	13.11	6.94	0.00	-952254.44	-46.06	0.03	0.16
Lower Quartile	Issuer Total	17.43	93.99	0.14	1.21	4.00	0.51	19.21
	Non-Issuer Total	16.04	94.36	0.26	1.73	2.82	0.87	15.53
Median	Issuer Total	18.26	124.24	0.32	2.05	6.36	1.33	39.01
	Non-Issuer Total	16.86	125.72	0.51	4.00	5.60	1.70	35.37
Upper Quartile	Issuer Total	18.92	162.90	0.45	4.59	9.10	2.38	50.50
	Non-Issuer Total	17.84	185.96	1.10	14.91	10.96	2.70	63.55
Maximum	Issuer Total	22.06	931.59	3.95	147.59	38.28	3.85	91.96
	Non-Issuer Total	22.73	555.88	47.61	67807.75	43.88	16.45	99.27

Table 4 Balancing: Test Results. This table provides statistical tests regarding the differences in location, dispersion and distribution measures presented in Table 3 of the matched and total issuer/non-issuer samples across the variables used for estimating $\hat{P}(X)$ (see Table 1 for a list of definitions and calculations). The upper panel shows the balancing test results for the matched issuer and issuer samples and the lower panel shows the balancing test for the total (unmatched) issuer and non-issuers. The tests relate the significance of differences in the balancing descriptives in Table 3. Only p-values are provided with significance levels of $p < 0.01$, $p < 0.05$, $p < 0.1$ for '***', '**', '*' respectively

p-Value from		SIZ_{t-1}	LIQ_{t-1}	LEV_{t-1}	SOL_{t-1}	TPR_{t-1}	STO_{t-1}	AST_{t-1}
Test for Difference in Matched Sample ...								
Mean	t-Test	0.058*	0.067*	0.946	0.374	0.500	0.626	0.069*
Medians	Wilcoxon Test	0.058*	0.113	0.244	0.113	0.747	0.386	0.043**
Variances	F-Test	0.029**	0.000***	0.000***	0.000***	0.000***	0.002***	0.048***
Distributions	Kolmogorov-Smirnov-Test	0.047**	0.126	0.078*	0.196	0.735	0.196	0.047***
Std. Differences		0.366	0.354	0.013	0.171	0.129	0.093	0.350
Test for Difference in Total Sample ...								
Means	t-Test	0.000***	0.854	0.000***	0.369	0.789	0.000***	0.354
Medians	Wilcoxon Test	0.000***	0.845	0.000***	0.000***	0.626	0.029**	0.647
Variances	F-Test	0.314	0.000***	0.000***	0.000***	0.829	0.000***	0.066*
Distributions	Kolmogorov-Smirnov-Test	0.000***	0.421	0.000***	0.001***	0.119	0.134	0.275
Std. Differences		0.959	0.028	0.329	0.070	0.037	0.396	0.120

Fig. 3 QQ-Plots for Balancing. In this collection of QQ-plots, each row stands for one of the seven variables used in the model for $\hat{P}(X)$ (upper panel of Table 1). The left plot in each row compares the complete sample of 1872 non-issuers and 65 issuers on that variable. The right hand side shows the comparison in that dimension of our matched samples, with 55 issuers and 159 non-issuers. In all of the graphs, the issuer quantiles are plotted on the x-axis and the non-issuer quantiles on the y-axis. For presentational purposes, some extreme values have been winsorized

5 Results

We now come to the results of our analysis, the treatment effect, the question whether the bond issue in itself, controlling for confounding influences, had negative consequences for the issuers. We compare issuers and non-issuers' along five different P/L figures through the two-year period starting with the issue year. At first, we present the results from the main study as described in Sec. 3 before we show the results of several robustness checks.

5.1 Propensity Score Matching Results

The most important results regarding the outcome variables of the two matched samples are provided in Table 5. Following Imai et al (2008), we analyze the differences via a *t*-test regarding the differences in the means of the matched samples. Further statistics are provided in Table 5, like tests regarding the median, variance and distribution. Given the results for the two location measures mean and median, we find evidence for a deterioration of P/L figures after the issue in general. Most importantly, *TPR* and *ROA* go down significantly in both the issue and the post-issue year, when we compare issuers to a group of non-issuers who were very similar to them pre-issue. So, even before going into further detail, there was a significant downswing in net income relative to firm size among issuers. A decrease in net income reduces the distributable amount for shareholders and could even lead to default when interest payments cannot be made to debtholders.

Now the result that *TPR* and *ROA* go down for issuers, when seen for itself is hardly surprising, given the many defaults observed over the past few years within the SME bond segment. Its worth noting however, that *TPR*, which includes interests, is quite stable in the issuance year, before going down significantly in the post-issue year. Therefore, we look at the other outcome variables in Table 5. We start with *STO* and *OPM*. Both are measures of operating performance. The former of how much sales are generated per unit of size and the latter essentially relating sales to costs, as *EBIT* is sales minus operating costs. We show that *STO* and *OPM* are both more negative in tendency and/or significantly for bond issuers relative to non-issuers. This is a somewhat surprising result as the issuance in itself is a financing event after all and the link to an operating figure like sales and/or *EBIT* is unclear. A downswing in operating performance could be associated with (proportional to total assets) declining marketing activities, with products and services going out of fashion or with another change on the demand side like a decrease in available income within the target population. Additionally, any increase in costs could explain the (in tendency) decrease of the *OPM*. Seeing a firm as a pool of limited resources available to accomplish specific tasks, the increase in financing activities (planning, preparing, advertising, executing and monitoring the bond issuance) can lead to a relative negligence of other, sales-generating and cost-cutting processes. The lower operating margin could also be related to a larger administrative overhang from the issuance and other costs related to it. We also think that firms, in possession of private information about future developments on the sales and cost side, could try to rise

Table 5 Treatment Effect Significance Tests. This table provides the results of statistical tests regarding the differences in location, dispersion and distribution measures of the matched issuer/non-issuer samples across the outcome variables. The issuer sample contains all issuers ($n = 55$) for whom at least one match was available. The non-issuer sample contains all control matches ($m = 159$) assigned to treatment units. The columns refer to the outcome variables for the issue year (t_0) and the subsequent year (t_1). The meaning of variable abbreviations and their calculation are found in the lower panel of Table 1. The differences in the table refer to the issuer group values minus the non-issuer group values, e.g. a negative value indicates a negative treatment effect. p -values are condensed and refer to $p < 0.01$, $p < 0.05$, $p < 0.1$ for '***', '**', '*' respectively in the same row as the statistic with the exact p -values also shown in brackets below the statistic they refer to

Value	TPR_0	TPR_1	ROA_0	ROA_1	STO_0	STO_1	OPM_0	OPM_1	INT_0	INT_1	TXE_0	TXE_1
Test for Differences in												
Mean	-0.012	-0.032***	-0.021**	-0.050***	-0.477***	-0.332**	0.003	-0.009	0.105	0.236	0.155	-0.081
Means												
t-Test p -Value	(0.211)	(0.005)	(0.028)	(0.000)	(0.001)	(0.029)	(0.850)	(0.605)	(0.357)	(0.111)	(0.185)	(0.614)
Median	-0.011	-0.027***	-0.025***	-0.044***	-0.591***	-0.452**	-0.008	-0.014*	0.071	0.210	0.080	-0.035
Medians												
Wilcoxon	(0.124)	(0.002)	(0.008)	(0.000)	(0.001)	(0.011)	(0.266)	(0.057)	(0.258)	(0.104)	(0.447)	(0.986)
Test p-Value												
Variance	0.013**	0.041***	0.012*	0.041***	0.088	0.243**	0.057***	0.060***	0.405***	0.746***	0.330***	0.486***
Variances												
F-test p -Value	(0.050)	(0.000)	(0.069)	(0.000)	(0.377)	(0.022)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Distribution	0.002	0.003***	0.345***	0.509***	0.339***	0.255**	0.208	0.309***	0.244*	0.345***	0.150	0.182
KS-Test statistic												
KS-Test p -Value	(0.293)	(0.008)	(0.002)	(0.000)	(0.003)	(0.047)	(0.167)	(0.008)	(0.065)	(0.002)	(0.539)	(0.293)

external debt just before the downswing actually happens. From that perspective, the issuance would be a negative signal to the market.

From operating aspects forward, we come to *INT*, proceeding in the way a P/L statement is usually presented. Interest expenses are a very important measure here as the bond issue, a financing event, has a strong influence on them. For *INT*, the issuers' median is significantly higher in both years. This finding implies that comparable non-issuers are able to obtain cheaper capital, despite the high promised coupon payments, little discussion whether the German SME bond market was actually an attractive way of refinancing. We find at least a tendency that this was not the case. Coupon payments were very high and further research could be directed here to provide a clearer picture.

From sales to EBIT and interest expenses, we have now arrived at EBT, or earnings before taxes. Between this measure and net income, taxes and extraordinary expenses are deducted. This part of the P/L statement is analyzed using *TXE*. Taxes should not make a huge difference, as all firms in our sample must obey to the same, e.g. the German, tax authorities. However, extraordinary expenses can be important for the analysis as firms could try to pass certain expenses into this part of the P/L statement to have better operating figures to present (e.g. EBIT). We cannot find a significant difference in locations for *TXE*. This is significant as fraudulent behavior and creative accounting methods are natural first suspects whenever a market fails for apparently no good reason. Both, and especially the latter, would however necessitate the bypassing of expenses into the extraordinary segment and since there is no clear increase or decrease in *TXE* for issuers relative to non-issuers, we cannot find evidence for such a behavior.

All outcome variables analyzed so far are ratios. Obviously, the change in a ratio may either be driven by a change in the numerator, the denominator, or both. In our context, this observation raises the concern that the decline in the outcome variables may be driven by the balance-sheet increasing effect of the financing event, and thus, that the significant increase of total assets in the issuance period will impact ratios mechanically. Raising debt will increase total assets immediately, whereas improvements in operating performances will be delayed until the investment projects start to amortize. To address this concern, we take a more detailed look at the developments of the numerators of *TPR*, *ROA* and *STO*, always relative to the non-issuer sample. Instead of ratios scaled by total assets, we consider the relative annual change in total profitability, net income, EBIT, etc as outcome variables, defined as $\Delta Y_t = (Y_t - Y_{t-1})/Y_{t-1}$. Results are summarized in Table 6.

The first two columns confirm that within the issuance year, the issuers expand their balance sheet, i.e. we find a significant positive difference in the change of total assets between t_{-1} and t_0 , while no significant changes in total assets occur in the post-issuance year (i.e. between t_0 and t_1). Thus, a mechanical effect on ratios cannot be ruled out from this observation. However, looking at the changes in the numerators in the following columns, we clearly see that the decline in ratios is not materially affected by the increase in total assets in the post-issuance year. We find significant negative values for all of the four proxies of operating performance: Total profits, net income, EBIT and Cashflow. Only the relative change in sales turns out to be positive, which suggests that issuers, which expanded their asset base, were

Table 6 Treatment Effect Significance Tests – Ratio Components. This table provides the results of statistical tests regarding the differences in location measures of the matched issuer/non-issuer samples across the components of the outcome variable ratios (plus Cashflow). The issuer sample contains all issuers ($n = 55$) for whom at least one match was available. The non-issuer sample contains all control matches ($m = 159$) assigned to treatment units. The columns refer to the components of the outcome variables for the issue year (t_0) and the subsequent year (t_1). The variables refer to the components found on the right hand side of the lower panel of Table 1. The differences in the table refer to the issuer group values minus the non-issuer group values, e.g. a negative value indicates a negative treatment effect. p -values are condensed and refer to $p < 0.01$, $p < 0.05$, $p < 0.1$ for ***, **, * respectively in the same row as the statistic with the exact p -values also shown in brackets below the statistic they refer to

Value	Δ Total Assets $t-1, t_0$	Δ Total Assets t_0, t_1	Δ Total Profits t_0, t_1	Δ Net Income t_0, t_1	Δ Sales t_0, t_1	Δ EBIT t_0, t_1	Δ Interest t_0, t_1	Δ Taxes & Extraord. t_0, t_1	Δ Cash-flow t_0, t_1
Test for Differences in									
Mean	Difference in Means	0.01*** (0.00)	0.00 (0.58)	-0.26 (0.51)	-0.81** (0.03)	0.08** (0.03)	-0.17 (0.62)	0.05 (0.95)	-0.52* (0.08)
Median	Difference in Medians	0.01*** (0.00)	0.00 (0.27)	-0.65* (0.06)	-0.68** (0.04)	0.06** (0.04)	-0.37** (0.05)	-0.13 (0.69)	-0.64*** (0.00)
Variance	Difference in Variances	0.01*** (0.00)	0.00*** (0.00)	1.66*** (0.00)	1.59*** (0.00)	0.17*** (0.00)	1.42*** (0.00)	0.52*** (0.00)	1.20*** (0.00)
Distribution	F-test p -Value	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	KS-Test statistic	0.65*** (0.00)	0.24* (0.08)	0.35*** (0.00)	0.40*** (0.00)	0.36*** (0.00)	0.32*** (0.01)	0.18 (0.29)	0.42*** (0.00)

able to generate more sales. However, combined with the result that EBIT declines, their operating profit margin is negatively affected. It further suggests, that since EBIT declined although higher sales were generated, the firm must have incurred significantly higher costs.

Regarding interest payments, we find, unsurprisingly, a strong relative increase in interest expenses (Δ Interest), which drives the decline in the ratio *INT*, and which is further aggravated by the declining EBIT. *TXE* was found to be stable as a ratio and taxes and extraordinary items are also fairly stable as relative changes although there was a tendency of a decrease here in the issuance year. This could indicate a strategic shift of extraordinary items to later post-issuance years and certainly merits further investigation. It is worth noting that all the results here are relative developments seen from the matched issuers compared to their non-issuer counterparts, e.g. the average change in a value of issuers minus the average change among non-issuers.

When taken as a whole, we see that issuer firms had severe overall downswings, as measured by *TPR* and *ROA*. Our separated analysis shows that not only did interest expenses increase strongly, issuers also suffered significant decreases in relative operating efficiency. Issuing firms show a decline in proxies for economic performance such as total profitability, net income, EBIT and cash flows. Furthermore, there was a slight tendency of an increase in costs. Coupled with an increasing interest burden, many factors jointly contributed to the problems faced by SME bond issuers in Germany, but they were not restricted to the financing side.

5.2 Separating Issuers by Use of Bond Proceeds

How are firms using the proceeds of the issuance and does this choice impact their post-issuance performance? To answer this question, we manually collected data from the bond indentures about the intended use of proceeds and split issuers in two groups: Those who mainly stated to use the proceeds for refinancing and those who stated to use them mainly for investment.¹² We then calculated the treatment effect of the issuance for both groups comparatively to their respective matches among non-issuers.

The results can be found in Tables 7 and 8. They show that, while behaving similarly on the surface, there are several interesting differences between how the firms in the investment group (in the upper panel in both tables) performed relative to a matched non-issuer sample and how firms in the refinancing group (in the lower panel in both tables) did relative to a non-issuer sample matched to them. The most notable results are that while the ratios develop similarly (see e.g. *TPR* and *ROA*), one can confirm a significant downswing in EBIT for the panel of investors, but not for the refinancing panel. Furthermore, we find that interest expenses carry a positive coefficient in both panels, but the increase appears stronger among the investment panel, suggesting that firms which use bond proceeds for refinancing face a less pronounced increase in their interest burden. The result appears in line

¹² One has to keep in mind, that the standards for the investment prospectus were low and a prospectus liability was not given. Thus, the information has to be handled with caution and does not necessarily reflect the actual use of the proceeds.

Table 7 Separating Issuers by Use of Proceeds: Treatment Effect Significance Tests. This table provides the results of statistical tests regarding the differences in location measures of the matched issuer/non-issuer samples across the outcome variables for the robustness check concerned with the main driver for the issuance process, e.g. investment or refinancing. The upper panel shows the results of issuers ($n = 30$) primarily using the bonds proceeds for investment/growth, whereas the lower panel represents issuers ($n = 18$) who used the bond proceeds for refinancing. The columns refer to the outcome variables for the issue year (t_0) and the subsequent year (t_1). The meaning of variable abbreviations and their calculation are found in the lower panel of Table 1. The differences in the table refer to the issuer group values minus the non-issuer group values, e.g. a negative value indicates a negative treatment effect. p -values are condensed and refer to $p < 0.01$, $p < 0.05$, $p < 0.1$ for '***', '**', '*' respectively in the same row as the statistic with the exact p -values also shown in brackets below the statistic they refer to. Balance was monitored and found to be satisfactory in both studies

Test for Differences in	Value	TPR_{t_0}	TPR_{t_1}	ROA_{t_0}	ROA_{t_1}	STO_{t_0}	STO_{t_1}	OPM_{t_0}	OPM_{t_1}	INT_{t_0}	INT_{t_1}	TXE_{t_0}	TXE_{t_1}
INVESTMENT PANEL													
Mean	Difference in Means	-0.02 (0.28)	-0.04*** (0.01)	-0.03*** (0.05)	-0.06*** (0.00)	-0.91*** (0.00)	-0.80*** (0.00)	0.05*** (0.05)	0.00 (0.99)	0.18* (0.08)	0.38*** (0.04)	0.01 (0.97)	-0.03 (0.85)
Median	Difference in Medians	-0.01	-0.03***	-0.03***	-0.06***	-1.04***	-0.77***	0.02	-0.02	0.04*	0.20**	0.01	0.14
	Wilcoxon Test p -Value	(0.39)	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)	(0.33)	(0.12)	(0.09)	(0.05)	(0.78)	(0.53)
REFINANCING PANEL													
Mean	Difference in Means	-0.03*** (0.01)	-0.03*** (0.05)	-0.05*** (0.00)	-0.06*** (0.00)	-0.96*** (0.00)	-0.70*** (0.02)	-0.02 (0.27)	0.00 (0.93)	0.06 (0.74)	0.24 (0.23)	0.21 (0.30)	0.20 (0.43)
Median	Difference in Medians	-0.04**	-0.03*	-0.05***	-0.05***	-0.95***	-0.32*	-0.02	-0.02	0.19	0.29***	0.05	0.08
	Wilcoxon Test p -Value	(0.03)	(0.07)	(0.00)	(0.00)	(0.01)	(0.06)	(0.13)	(0.40)	(0.27)	(0.04)	(0.85)	(0.66)

Table 8 Separating Issuers by Use of Proceeds: Treatment Effect Significance Tests – Ratio Components. This table provides the results of statistical tests regarding the differences in location measures of the matched issuer/non-issuer samples across the components of the outcome variable ratios (plus Cashflow). The issuer sample contains all issuers ($n = 55$) for whom at least one match was available. The non-issuer sample contains all control matches ($m = 159$) assigned to treatment units. The columns refer to the components of the outcome variables for the issue year (t_0) and the subsequent year (t_1). The variables refer to the components found on the right hand side of the lower panel of Table 1. The differences in the table refer to the issuer group values minus the non-issuer group values, e.g. a negative value indicates a negative treatment effect. p -values are condensed and refer to $p < 0.01$, $p < 0.05$, $p < 0.1$ for ‘***’, ‘**’, ‘*’ respectively in the same row as the statistic with the exact p -values also shown in brackets below the statistic they refer to

Test for Differences in	Value	Δ Total Assets t_{-1}, t_0	Δ Total Assets t_0, t_1	Δ Total Profits t_0, t_1	Δ Net Income t_0, t_1	Δ Sales t_0, t_1	Δ EBIT t_0, t_1	Δ Interest t_0, t_1	Δ Taxes & Extraord. t_0, t_1	Δ Cash-flow t_0, t_1
INVESTMENT PANEL										
Mean	Difference in Means	0.01***	0.00	-0.41	-0.68	0.07	-0.76**	0.81***	-0.18	-0.78***
	t-Test p -Value	(0.00)	(0.38)	(0.29)	(0.28)	(0.18)	(0.03)	(0.00)	(0.82)	(0.01)
Median	Difference in Medians	0.01***	0.00	-0.56*	-1.08*	0.05	-0.49***	0.36***	0.28	-1.12***
	Wilcoxon Test p -Value	(0.00)	(0.45)	(0.08)	(0.07)	(0.22)	(0.01)	(0.00)	(0.98)	(0.00)
REFINANCING PANEL										
Mean	Difference in Means	0.01**	0.00	0.03	-1.02**	0.08	0.73	0.14	2.98	-0.53
	t-Test p -Value	(0.01)	(0.90)	(0.96)	(0.05)	(0.11)	(0.14)	(0.48)	(0.12)	(0.26)
Median	Difference in Medians	0.01***	0.00	-0.62	-0.55	0.10*	0.10	0.16	0.08	-0.62
	Wilcoxon Test p -Value	(0.01)	(0.71)	(0.19)	(0.16)	(0.08)	(0.72)	(0.12)	(0.37)	(0.12)

with intuition as refinancing firms stated their goal to retire outstanding debt. Given that interest expenses still increased (albeit not statistically significant), it seems that refinancing firms were not able to overall lower their costs of debt financing. In interpreting the results, one has to keep in mind that the number of observations is relatively small (in particular for the refinancing panel). However, overall the results conditional on the use of proceeds suggest the interpretation that investing firms suffered greater operational downturns which may be the result of inefficient investments and greater costs. On the other hand, it appears that refinancing firms were unsuccessful in lowering their cost of capital.

5.3 Sensitivity and Robustness

As a last step, we run sensitivity and robustness checks. For robustness, we calculate treatment effects using different models and other variations of the propensity score methods. This will include an OLS regression as a completely different approach with T as a dummy for issuance and propensity score variations on the set of variables in X , varying identification and treatment of outliers (common support), differing estimation of propensity scores $\hat{P}(X)$, conditioning methods on $\hat{P}(X)$, caliper widths and matching algorithms. This should ensure that our modeling choices of and within the propensity score method are not influencing the results.

5.3.1 Robustness I: Linear Regression

Before evaluating our specific choice of the propensity score method, we check whether a completely different approach (following for example Smith and Todd 2005) confirms our results as to how firms fared after the issuance. Therefore we used the financial research standard, a linear regression model on the covariates (X) in the upper panel of Table 1, with added year and sector dummy variables and T as independent variables. The P/L figures from the lower panel of Table 1 as dependent variables (Y) in separate regression models. Details on this variant can be found in Table 9. We find a significant negative relationship between ROA and being an issuer over the issue year and the following year. When controlling for X and fixed year effects, there is also a significant negative relationship between STO and T . For OPM , INT and TXE , the regression model shows no significant treatment effects.

5.3.2 Robustness II: Matching on t_{-2} and t_{-1}

In the main study, we only matched issuers to non-issuers based on the issuers pre-issue (t_{-1}) year. The balance sheet data of one year can fluctuate for many reasons. Thus, we conduct a robustness study where we matched issuers and non-issuers on the years t_{-2} and t_{-1} and used otherwise a very similar propensity score matching method as in the main study. We present the results from a version without explicit sector controls because in this setting (with already such a high-dimensional

X), sample size becomes a concern.¹³ Table 10 shows the treatment effect results for this robustness check when considering one more year before the issue for the matching process. We draw conclusions which are very similar to those from the main study here. *TPR* and *ROA* are lower in the years after the issuance, and the same holds for *STO*. There is a slight trend for *OPM* to be lower for issuers ex-post and a tendency for higher observed values of *INT*. *TXE* is, like in the main study, insignificant. Because it is much more complicated to match on 14 variables and to present results, we prefer the simplicity of the main study with only the pre-issue year included. Data availability constraints limit our ability to match firms with even more years pre-issue. Similarly, we cannot (without losing a majority of observations) evaluate the *outcome* variables over a period of three or more years. Overall, we conclude that our results were not influenced by short-term trends in the year before the issuance.

5.3.3 Robustness III: Different Propensity Score Model Configurations

The sensitivity checks here analyze whether our specific variant of the propensity score method influenced the results. We run the same analysis with multiple different configurations and parametrizations of the propensity score method. Table 11 shows the treatment effect estimates for the variants we have considered. We changed how $P(X)$ is estimated, how common support is evaluated and how propensity scores are used to condition the sample. In case they were used for matching, we implemented several variants of matching as well. Overall, we do not find strong differences between the results of our main study in Table 5 and the results of the PS variants in Table 11. In general, the variants point into a very similar, almost identical direction as we find further supporting evidence for issuers *TPR*, *ROA*, *STO* as well as *OPM* being smaller after the issuance, while *INT* is higher up and *TXE* relatively similar. The results of this subsection are reassuring because Zhong (2008) showed that when unconfoundedness holds, so the two groups are truly balanced across the used covariates, the estimation of treatment effects is not sensitive to the specifications within the propensity score model.

Since neither our choices within the propensity score matching method, nor the choice of using only variables in t_{-1} , nor the selection of propensity scores in the first place altered our conclusions significantly, we gain further confidence that issuer firms faced economic problems that coincided and were probably related to the issuance in itself instead of their endowment of X being the primary culprit.

6 Conclusion

The market segment of German SME bonds or (mini-bonds) was welcomed with much enthusiasm in 2009/10, but turned into a more than disappointing experience within only few years. After the fact, many commentators in particular in the public

¹³ In an unreported study, we did run the same model with sector controls and find qualitatively similar results.

Table 9 Robustness I: Linear Regression Model. This table shows the results for two separate linear regressions of the following equation $Y = \beta_0 + X\beta_X + T\beta_T$ (plus year and sector dummies). See Table 1 for the definition and calculation of the variables in X and Y . We report the coefficients for the factors with indicated significance values. Data was winsorized at 0.01 & 0.99 percentiles and control observations containing at least one covariate value exceeding the issuer range by more than 25% were excluded. The rows represent independent variables whereas the columns show individual regression models with the corresponding dependent variable. A Breusch-Pagan test was used to detect conditional heteroskedasticity and in case of it being present, White's Standard Errors were used to correct for it. Variance inflation factors were used to evaluate the influence of multicollinearity and it was found to be not relevant for neither model. Significance levels are indicated for $p < 0.001$, $p < 0.01$, $p < 0.05$ with '****', '**', '*' respectively

Ind. Var.	TPR_0	TPR_1	ROA_0	ROA_1	STO_0	STO_1	OPM_0	OPM_1	INT_0	INT_1	TXE_0	TXE_1
T	-0.02**	-0.04****	-0.04****	-0.06****	-0.40**	-0.31**	-0.02*	0.00*	0.23*	0.49****	0.20	0.02
SIZ	-3.45*	-1.94	-0.02	-0.01	0.15	0.22	0.03**	0.02*	-0.13	-0.04	0.05	0.05
LIQ	0.10	0.17	0.00	0.00	-0.21**	-0.21***	0.02***	0.02***	0.11***	0.07*	0.05	-0.01
LEV	-0.42***	-0.42***	0.00	0.00	-0.06***	-0.06***	-0.02***	-0.02***	-0.13***	-0.11***	-0.07**	-0.05*
SOL	0.02***	0.01**	0.00***	0.00***	0.00**	0.00*	0.00***	0.00***	0.00***	0.00**	0.00	0.00
TPR	0.62***	0.55***	0.01***	0.01***	-0.01***	-0.01***	0.00***	0.00***	0.00	0.00	0.00*	0.00
STO	-0.03	-0.21	0.00	0.00	1.41***	1.36***	-0.03***	-0.03***	-0.06***	-0.07***	-0.05*	-0.07**
ACT	0.00	0.00	0.00***	0.00*	0.00**	0.00**	0.00***	0.00***	0.00***	0.00	0.00	0.00
Year-Dummy												
Sector-Dummy												
Intercept	-0.22	-10.26	-0.02	-0.12	3.20**	3.00**	-0.11	-0.61***	0.26	-1.08	-4.92***	0.16
R^2	0.47	0.34	0.47	0.34	0.68	0.67	0.34	0.30	0.04	0.04	0.01	0.01
Adj. R^2	0.46	0.34	0.47	0.34	0.68	0.67	0.34	0.29	0.04	0.03	0.01	0.00
F-test p -value	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***	0.00**

Table 10 Robustness II: Treatment Effect Significance Tests. This table provides the results of statistical tests regarding the differences in location, dispersion and distribution measures of the matched issuer/non-issuer samples across the outcome variables for the robustness check using variables from the years $t-1$ and t_0 . The issuer sample contains all issuers ($n = 59$) for whom at least one match was available. The non-issuer sample contains all control matches ($m = 175$) assigned to treatment units. The columns refer to the outcome variables for the issue year (t_0) and the subsequent year (t_1). The meaning of variable abbreviations and their calculation refer to those in the lower panel of Table 1. The differences in the table refer to the issuer group values minus the non-issuer group values, e.g. a negative value indicates a negative treatment effect. p -values are condensed and refer to $p < 0.01$, $p < 0.05$, $p < 0.1$ for '***', '**', '*' respectively in the same row as the statistic with the exact p -values also shown in brackets below the statistic they refer to

Test for Differ- ences in	Value	TPR_1	ROA_0	ROA_1	STO_0	STO_1	OPM_0	OPM_1	INT_0	INT_1	TXE_0	TXE_1
Mean												
Difference	-0.006	-0.042**	-0.025***	-0.048***	-0.382***	-0.326**	-0.005	-0.006	0.252	0.364	0.090	0.092
in Means												
t-Test p -	(0.867)	(0.011)	(0.009)	(0.000)	(0.004)	(0.018)	(0.824)	(0.790)	(0.258)	(0.158)	(0.704)	(0.655)
Value												
Median												
Difference	0.000	-0.019**	-0.020***	-0.029***	-0.448***	-0.212**	-0.023	-0.020*	0.112	0.212*	-0.099	0.033
in Medians												
Wilcoxon	(0.779)	(0.020)	(0.009)	(0.000)	(0.005)	(0.013)	(0.198)	(0.093)	(0.145)	(0.094)	(0.170)	(0.769)
Test p -												
Value												

Table 11 Robustness III: Other Propensity Score Configurations. This table provides the differences in medians of the conditioned issuer/non-issuer samples across the outcome variables for several alternative configurations of the propensity score method. The columns refer to the outcome variables for the issue year (t_0) and the subsequent year (t_1). The meaning of variable abbreviations and their calculation refer to those in the lower panel of Table 1. The differences in the table refer to the issuer group values minus the non-issuer group values, e.g. a negative value indicates a negative treatment effect

Configuration	TPR_0	TPR_1	ROA_0	ROA_1	STO_0	STO_1	OPM_0	OPM_1	INT_0	INT_1	TXE_0	TXE_1
Logit, Density CS Check on $\hat{P}(X)$, Greedy 1:1 Matching, Fixed Caliper (0.02)	-0.031	-0.031	-0.014	-0.038	-0.120	-0.243	-0.022	-0.013	0.204	0.277	-0.046	-0.131
Probit, Upper-Lower Trim CS Check on $\hat{P}(X)$, Optimal 1:1 Matching, Fixed Caliper (0.05)	-0.010	-0.027	-0.029	-0.051	-0.346	-0.212	-0.020	-0.041	0.095	0.328	-0.055	-0.163
Logit, No CS Check, Greedy 1:5 Matching, Austin Caliper	-0.024	-0.031	-0.028	-0.048	-0.354	-0.281	-0.033	-0.044	0.144	0.102	0.071	-0.055
Probit, 3-Criteria CS on X, Greedy 3:6 Matching, Austin Caliper	-0.019	-0.028	-0.027	-0.055	-0.208	-0.125	-0.028	-0.036	0.118	0.166	-0.027	-0.082
Boosted Trees, 3-Criteria CS on X, Stratification ($s = 5$) on $\hat{P}(X)$	-0.006	-0.028	-0.016	-0.045	-0.379	-0.226	0.006	-0.006	0.182	0.201	0.060	-0.131
Boosted Trees, 3-Criteria CS on X, Simple Weighting on $\hat{P}(X)$	-0.011	-0.031	-0.022	-0.050	-0.543	-0.406	0.016	0.003	0.178	0.314	0.112	-0.086

media were quick to point out that the failure should have been foreseeable. Claims that were partly confirmed by few academic research articles. However, we believe that hindsight bias is a crucial concern in such an evaluation and therefore the focus of our contribution is to provide an analysis which is particularly careful in constructing an appropriate comparison sample. Thus, we dedicate a substantial part of our contribution on the methodical aspect of showing how to choose a control sample which is as similar as possible to the sample of issuing firms. Secondly, we have access to an extensive pool of potential control companies by being able to draw on the proprietary database of Creditreform.

As a main result, we find interesting differences in the post-issuance performance between the sample of issuing firms and the matched sample of non-issuers. First, issuers display a decline in their net income. While this result may have been expected due to the fact of a substantially higher interest burden (even though total profitability, which includes interest, also goes down), our most interesting finding is that issuing companies also display a substantially lower operating performance as shown by a decline in proxies for the economic performance such as total profitability, net income, EBIT and cash flows. Our findings are in line with the many empirical studies in the literature which find that security issuers have operating performance downswings after the issuance.

Our findings have implications for the discussion to what extent the poor performance of the mini bond market could have been foreseeable. By putting the emphasis on constructing a comparison sample which is *ex ante* (statistically) indistinguishable but shows different results *ex post*, it can be concluded that a substantial part of the comparatively poor development in operating performance of issuing companies was apparently not predictable from the financial information before the issuance.

Further insight is gained by separating issuers by their use of bond proceeds. Here we find evidence for firms, which are undertaking significant investments, suffering from operating problems. This could imply, at best, that these are projects with long time horizons and very asynchronous cost/return profiles. At worst, these projects were of questionable quality.

Our results come with several things to keep in mind. First, due to the delay in reporting and collecting financial statement data, we have to restrict our findings for our available sample, e.g. all German SME bond issuers which issued until and including 2013. Second, we restrict attention to information from financial statement data and sector membership. One could argue that many other variables could play a vital role for such an analysis. However, financial statement information is without doubt one of the key ingredients in any company evaluation. So, our approach is likely to capture the major dimension of company performance. Finally, although we implement a sophisticated method to construct an appropriate comparison sample, the method is not guaranteed to be unbiased. An interesting limitation is described in Heckman et al (1998a); Heckman, Ichimura, Smith, and Todd (1998a), who state that the simple framework as was utilized here does not incorporate general equilibrium effects, so that the payoff from issuing bonds to each individual entity does not depend on the overall number of issuing firms. It is easily conceivable how boom periods with high supply and demand or periods with severe oversupply of bonds could alter bond issuance and post-issue performance.

Further research could be directed to identify other factors, beyond operating figures, which had an influence on issuer defaults. Market wide forces, investor sentiment in a probably very emotional segment (“The German Mittelstand”), changes in the legal system (a new law was introduced in Germany which redefined certain parameters of insolvency and bankruptcy procedures) could be interesting to analyze in response to the issuer defaults. Naturally, cases of outright fraud (not detectable by looking at *TXE*) and their impact as well as market timing, market learning, market innovation are all possible avenues for further research.

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