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ARTICLE

Do firms hedge in order to avoid financial distress costs? New empirical evidence using bank data

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Abstract

We present a new approach to test empirically the financial distress costs theory of corporate hedging. We estimate the *ex-ante* expected financial distress costs, which serve as a starting point to construct further explanatory variables in an equilibrium setting, as a fraction of the value of an asset-or-nothing put option on the firm's assets. Using single-contract data of the derivatives' use of 189 German middle-market companies that stems from a major bank as well as Basel II default probabilities and historical accounting information, we are able to explain a significant share of the observed cross-sectional differences in hedge ratios. Hence, our analysis adds further support for the financial distress costs theory of corporate hedging from the perspective of a financial intermediary.

KEYWORDS
bankruptcy costs, corporate hedging, financial distress, derivatives

JEL CLASSIFICATION
G2, G32, G33, D81

1 | INTRODUCTION

From Smith and Stulz (1985) there has been a continuously growing literature dealing with the questions why and how firms should use derivative instruments to reduce the variability in their income cash flows. Economic theories of corporate hedging are based on taxes, agency costs and costs of bankruptcy or—in a wider sense—costs of financial distress (FDC) as the main market imperfections, whose management may result in value increases for the firm's stakeholders.[1] Bartram (2000) and Aretz and Bartram (2010) provide a comprehensive overview of rationales for corporate hedging and the empirical literature testing these economic theories, which have up to now not been able to yield final conclusions regarding the explanatory power of the three different economic arguments:

- Tax reasons are due to rules that give rise to convexity in the taxation schedule and have been very thoroughly scrutinized for the US tax system (see e.g. Graham & Smith, 1999) but have overall accomplished only weak empirical support.
- Variables used to test whether corporate hedging can lower the agency costs resulting from shareholder–bondholder or shareholder–manager conflicts lead to fairly mixed results with only a small number of proxies (e.g. R&D expenditures) showing the predicted effects.
- There are quite many studies that contribute to the existing empirical evidence with regard to FDC, see e.g. Nance, Smith, and Smithson (1993), Mian (1996), Géczy, Minton, and Schrand (1997) and Chen and King (2014). Various proxy variables—like the (long-term) debt ratio, the short-term liquidity ratio and the interest coverage ratio, credit ratings or credit spreads—have been employed as substitutes for the expected FDC, which cannot be directly observed, and could sometimes be identified as statistically significant. However, there is up to now no paper in the hedging literature that tries to estimate directly FDC, which is the economic explanatory variable according to finance theory, on the basis of a structural model (cf. e.g. Glover (2016), who uses a similar approach to analyze the firm's capital structure decision).

In this paper, we provide a fresh perspective on the question if firms hedge in order to avoid *ex-ante* expected FDC. We estimate FDC as a fraction of an asset-or-nothing put option and further introduce a trade-off between FDC and transaction costs to calculate optimal hedge ratios. Using a proprietary dataset stemming from a major German bank comprising over-the-counter (OTC) derivative deals from 189 German middle-market companies, we find both variables to explain a significant share of the observed cross-sectional differences in hedge ratios based on both nominal and market values. To be more specific, we contribute to the literature in two main aspects:

Firstly, we come up with a novel estimation approach for the *ex-ante* expected FDC as an explanatory variable that is much more closely tied to corporate finance theory than the previous literature. The basic idea is to construct an empirical measure of the differences in *ex-ante* expected FDC that can be directly used as an explanatory variable for the observed cross-sectional differences in samples of companies' derivatives usage. Our estimation approach is based on the Merton (1974) structural model of debtholder default and makes use of the analytical formula for an "asset-or-nothing put option", which allows us to compute FDC as a fraction of the value of total assets.

We are able to show empirically that this measure of firm-specific *ex-ante* FDC is superior to the use of the traditional proxy variables, like the debt ratio, the interest coverage ratio and the short-term liquidity ratio, whose choice is rather ad hoc and is not based on a solid theoretical underpinning. Moreover, the new explanatory variable lends itself to be further exploited within an equilibrium setting that leads to an additional type of explanatory variables: In order to determine its optimal hedge ratio, each firm trades off its *ex-ante* expected FDC with the expected transaction costs (TC) that serve as a counterweight to prevent the firm from hedging as much as possible. As there are no systematic deviations in the transaction costs for derivatives hedging between firms (except for size issues), the cross-sectional differences between optimal hedge ratios in equilibrium should mainly be driven by differences in the firm-specific, marginal benefit of a further FDC reduction. We calculate both the absolute amount of expected FDC and the optimal

[1] FDC have both direct and indirect cost components (cf. e.g. Altman, 1984; Asquith, Gertner, & Scharfstein, 1994; Gruber & Warner, 1977; Weiss, 1990). While the direct costs of bankruptcy as a legal procedure, e.g. attorney fees, are considered to be relatively small, the indirect costs, such as more expensive financing or loss of market shares (Opler & Titman, 1994), are considered to be more relevant. Regarding highly leveraged transactions that become financially distressed, Andrade and Kaplan (1998) estimate FDC to be 10–20% of firm value. Using risk-adjusted default probabilities derived from corporate bond spreads, Almeida and Philippon (2007) quantify the net present value of FDC up to 13% of firm value.

hedge ratio for each firm in such an FDC–TC equilibrium and use them as our leading explanatory variables in a couple of linear regression models that build the empirical part of our paper.

Secondly, we enrich the existing knowledge about corporate hedging by testing our explanatory variables on a rich dataset from a major bank providing thus far unavailable information at the firm level. We analyze the usage of OTC interest rate and exchange rate (FX) derivatives in a sample of German middle-market companies on the basis of a proprietary dataset that stems from a major German bank. The credit risk in this market segment is generally non-investment grade so that the proper assessment of the risk of bankruptcy or default is crucial for the banks servicing this segment. From the firms' viewpoint, the threat of financial distress therefore should have a relevant magnitude.

The dataset contains all the existing derivative contracts that these companies had entered into with the bank at fiscal year-ends 2015 and 2014 and it provides us with single-contract level data. Hence, our dataset is different from those used in previous empirical studies in two main respects: On the one hand, our information on the derivative contracts used is far more granular, but on the other hand, the firms might have also entered into OTC derivatives contracts with other banks, which stay hidden from our eyes. As the probability that a firm does derivatives business with more than one bank is supposed to increase with company size, we pay special attention to size as a control variable. Because of the construction of our proprietary dataset, we are able to exploit the bank‘s internal rating data and the resulting regulatory "Basel II" PDs for the firms in the sample as well as the corresponding balance sheet data that are processed as a part of the rating system. Since the previous studies have been fairly restricted in terms of data availability, access to a large set of companies‘ derivative contracts opens up a new perspective on corporate hedging, namely that of a financial intermediary.

While the literature dealing with expected financial distress as an incentive for corporate hedging mostly covers the US market (see again Aretz and Bartram (2010) for an overview), there are only a few studies taking the hedging activities of German firms into account. In an extensive international study, Bartram, Brown, and Fehle (2009) analyze 7319 non-financial companies from 50 countries covering over 80% of the overall global market capitalization of non-financial firms. Surprisingly, their empirical findings frequently run counter to the usual theoretical predictions: Regarding the FDC hypothesis, for example, they find derivative users to be larger and more profitable. However, they also find derivative users to have significantly higher leverage and fewer liquid assets, as suggested by the common theory. Carroll, O'Brien, and Ryan (2017) investigate the determinants of derivative usage for non-financial firms from 11 European countries including Germany. They also find leverage to be a significant determinant of overall derivative usage. In line with these findings for European countries, Marsden and Prevost (2005) also find a positive relationship between the probability of financial distress and the use of derivatives for a sample of New Zealand listed companies. In an earlier study, Prevost, Rose, and Miller (2000) compare and contrast risk management practices of firms in New Zealand to those of firms in the considerably larger, more developed US, UK, and German markets. Among other findings, the authors conclude that New Zealand companies have many of the same reasons and objectives for using derivatives as firms in the much larger American and European economies.

Bodnar and Gebhardt (1999) were the first to compare the derivative usage of US and German companies by analyzing two surveys from both countries and matching companies based on size and industry: Their findings suggest that German firms are overall more likely to hedge and that US and German firms partly differ in their primary goal of hedging, their choice of instruments, and the influence of their market view when taking derivative positions. In a more recent study, Henschel (2006) and Henschel (2010) find German SMEs' hedging decisions to be clearly orientated toward the owner-manager and that a direct link between risk management and business planning is seldom found. In an earlier study for Germany, Glaum (2002) surveyed 74 non-financial firms' exchange rate risk management purposes: He finds that highly levered firms rather hedge and do not take bets or use selective risk management in line with the FDC hypothesis. Hence, it seems reasonable to take the analysis of the FDC hypothesis a step further when a new proprietary data source, namely the single-contract files of the derivative use of the corporate middle-market clients of a large German bank, is available. As the FDC hypothesis has been studied for other European markets as well (e.g. Judge (2006) finds strong evidence supporting the FDC hypothesis in a sample of 400 UK firms), we produce results that are also quite relevant in an international setting. Furthermore, we do not only contribute to the knowledge about the derivatives usage in the largest economy of the Eurozone, but the modeling approach presented generally allows for a refined analysis of the FDC hypothesis that seems applicable in other countries as well. It could similarly be applied to other national or international datasets whenever they entail a measure for the firm's PD that can be combined with leverage in an exogenous, Merton-style capital structure model. An example of such a potentially fruitful usage in future research would be, for example, the publicly available data from the European high-yield bond markets.

The remainder of the paper is structured as follows: In Section 2, we introduce our modeling framework and present the theoretical basis for our approach. Section 3 contains the empirical analysis, while the final section concludes.

2 | MODELLING FRAMEWORK

2.1 | Estimation of the FDC function

We consider a capital market with several firms, which are all-equity financed in the beginning. Each firm can choose to issue debt and to enter into derivative contracts. The stochastic future market value of their operating cash flows in t is called V_t and we assume for the sake of analytical tractability that V_t follows a geometric Brownian motion

$$V_t = V_0 e^{\left(\mu_V - \frac{\sigma_V^2}{2}\right)t + \sigma_V W_t}, \tag{1}$$

where μ_V denotes the drift-term, $\sigma_V > 0$ the volatility, and W_t a Wiener-process. Hence, V_t follows for fixed t a lognormal distribution with parameters $\mu = \ln(V_0) + (\mu_V - \frac{\sigma_V^2}{2})t \in \mathbb{R}$ and $\sigma = \sigma_V \sqrt{t}$. For reasons of simplicity, we limit this analysis to a one-period setting and denote $V := V_1$ and $\sigma = \sigma_V$. For $V \sim \mathcal{LN}(\mu, \sigma^2)$ the well-known probability density function, which is defined on $]0, \infty[$, is given by

$$f(V, \mu, \sigma) := \frac{1}{\sqrt{2\pi}\sigma V} e^{-\frac{(\ln(V)-\mu)^2}{2\sigma^2}} \tag{2}$$

and the corresponding cumulative distribution function is given by

$$F(V, \mu, \sigma) := \int_0^V f(x, \mu, \sigma) dx. \tag{3}$$

Following Merton (1974), we use a structural model of default. The firm can issue debt in $t = 0$. We denote the total amount, which is payable in $t = 1$ and which comprises both principal and interest, by $D > 0$. Assuming the drift term μ_V, V_0, D, and the probability of default are given, the volatility σ can be determined by solving

$$\begin{aligned} PD &= \Phi\left(-\frac{\ln\left(\frac{V_0}{D}\right) + \mu_V - \frac{1}{2}\sigma^2}{\sigma}\right), \\ \Leftrightarrow \quad \sigma &= \Phi^{-1}(PD) + \sqrt{\Phi^{-1}(PD)^2 + 2\left(\ln\left(\frac{V_0}{D}\right) + \mu_V\right)} \end{aligned} \tag{4}$$

where Φ denotes the cumulative distribution function of the standard normal distribution. Equation (4) provides a way to estimate the volatility of the asset value distribution, which is not a directly observable parameter, when the drift parameter μ_V, the firm's leverage, and an appropriate PD estimate are given.

We use the regulatory ("Basel II") probability of default (PD) of the companies to calculate the volatility parameter. The Basel II PD contains all the available information about the probability of a potentially distressed situation from a debtor's point of view and is a reliable source. We regard the Basel II default definition as an adequate way to distinguish between "bad" states of the world, in which the firm incurs costs of financial distress and those "good" states, where it does not.[2]

FDC arise when a firm is in or close to default. In the literature on corporate finance and corporate hedging, several alternative specifications of FDC functions can be found.[3] Following the mainstream literature on corporate hedging, we model FDC as a percentage portion of future firm value. We denote the FDC parameter, which we will assume to be firm-specific in the empirical study later on, by $\eta \in]0, 1[$ (Brennan & Schwartz, 1978; Leland, 1998; Ross, 1996). Assuming general risk-neutrality, which is rather common (cf. Castanias, 1983; Bradley, Jarrell, & Kim, 1984; Kale & Noe, 1990 or Kale, Noe, & Ramirez, 1991) in this type of analysis, the market value of FDC in $t = 0$ emerges as

$$FDC := \int_0^D \eta V f(V, \mu, \sigma) dV = \eta \mathrm{E}_0[V \mid V < D]. \tag{5}$$

According to option pricing theory, we can interpret the conditional expected value $\mathrm{E}(V \mid V < D)$ as the value of an asset-or-nothing put option. Given an underlying $S = V$ and a strike price $K = D$, this binary option has the payoff

$$S \text{ if } S \leq K, \quad or \quad 0 \text{ if } S > K. \tag{6}$$

Following Cox and Rubinstein (1985), its value is given by the first term of the Black–Scholes formula (Black & Scholes, 1973), which equals the unprotected present value of the underlying asset price conditional upon exercising the option. Cf. also Rubinstein and Reiner (1991). Hence, we can rewrite Equation (5):

$$FDC = \eta V_0 e^{-r_f} \Phi\left(-\frac{\ln\left(\frac{V_0}{D}\right) + r_f + \frac{1}{2}\sigma^2}{\sigma} \right). \tag{7}$$

With the exception of η, the parameters in (7) are either directly observable market data or can be calculated from the firm's PD via (4). We assume η to be a firm-specific parameter that can be inferred from a capital structure equilibrium which is given by a traditional static trade-off model. We introduce this capital structure model in Appendix A. For the optimally levered firm, η is given by Equation (A.5) in Appendix A, so that we can estimate the absolute amount of FDC for all firms according to (7).

2.2 | Implications of an FDC-induced hedging equilibrium

In this subsection, we analyze the testable implications of an equilibrium situation, in which all firms choose their optimal level of volatility considering the effects of a volatility reduction on the present value of their specific FDC.

[2] An internationally harmonized definition of a creditor default event was established for the first time in the Basel II accord (BCBS, 2005). This definition is based on the two general criteria (a) unlikeliness to pay and (b) contractual payment more than 90 days past due, which complement each other. It has been endorsed in 2006 into European Banking Law and is now encoded in Article 178 of the Capital Requirements Directive (CRR, 2013). The definition is much wider than the declaration of bankruptcy in a legal process and also entails situations with economic or accounting losses due to distressed restructurings. See also Purnanandam (2008) for a conceptual discussion on the differences between bankruptcy, insolvency, and financial distress. The implementation of the definition within banks' processes and IT systems has been closely monitored since the start of Basel II in 2007 by the national supervisory authorities in Europe.

[3] While Smith and Stulz (1985) and Stulz (1996) present graphical illustrations of costs of financial distress that increase with the extent of the firm's distress (cf. Turnbull (1979) and Dionne and Garand (2003)), Brown & Toft (2002) propose an exponential function and Turnbull (1979), Smith, Smithson, and Wilford (1989) and Cooper and Mello (1999) argue in favour of fixed FDC. Adam (2002) includes a fixed and a proportional component in his analysis.

Hedging is regarded as a means to reduce the volatility σ in the distribution of future asset value V. We assume that all firms have unrestricted access to a set of derivative contracts which are traded in frictionless market. Without any market frictions, the value of any hedging contract is zero at the time when it is written. By assuming an economy of risk-neutral agents, this translates into a zero effect on expected future cash flows. Hence, the effect of hedging on FDC is given by the following first partial derivative from (7) using the asset-or-nothing put option pricing formula:

$$\frac{\partial FDC}{\partial \sigma} = \eta V_0 e^{-r_f} \phi\left(\frac{\ln\left(\frac{D}{V_0}\right) - r_f - \frac{1}{2}\sigma^2}{\sigma}\right)\left(\frac{\ln\left(\frac{V_0}{D}\right) + r_f}{\sigma^2} - \frac{1}{2}\right) > 0 \tag{8}$$

if $D < e^{\mu} = V_0 e^{r_f - \frac{1}{2}\sigma^2}$.

Obviously, the FDC function of each firm is strictly increasing in firm value volatility σ_j, if its probability of default PD_j is below at least 50%. Hence, by costlessly reducing σ_j, hedging reduces the *ex-ante* expected FDC and increases firm value in these cases.

Since we assume a capital structure optimum independent of the hedging policy, the change in σ in Equation (8) stems directly from the use of a derivative instrument on the asset value distribution and shall not be misinterpreted as a change of σ resulting from a shift in leverage or PD that would have an indirect impact via Equation (4) and that would lead to a different comparative statics result.

What is new in our paper is that we give Equation (8) a cross-sectional interpretation, which we will state later on as a part of our main proposition: The marginal benefit of hedging by reducing FDC differs across firms: It depends on the firm's individual FDC parameter η, on its size V_0, on its exogenously given optimal debt ratio D_j/V_j, and on the corresponding probability of default PD_j, which enters (8) via σ_j (see (4)). Hence, the differences among firms' marginal benefits of FDC hedging can be measured using a set of firm parameters, that are either directly observable or that can otherwise be empirically estimated.

As a counterweight to FDC that prevents firms from transferring 100% of its hedgeable risk to the financial markets, we introduce transaction costs *TC* into the model, cf. Hahnenstein and Röder (2007) for a hedging model with transaction costs. The transaction cost function we assume is

$$TC = \gamma V_0(\sigma^* - \sigma), \tag{9}$$

where σ^* denotes the optimal firm value volatility after hedging. Thus, the difference $(\sigma^* - \sigma)$ denotes the reduction in volatility that goes along with the optimal hedging policy. The parameter $0 < \gamma < 1$ denotes the marginal transaction costs of hedging, which we assume to be constant across all firms. It can be interpreted as a basis point fee payable for each EUR of the derivative nominal that leads to the intended decrease in the absolute firm value volatility. The optimal (percentage) volatility σ^* that minimizes the sum of FDC and transaction costs is given by the following first-order condition as a unique solution:

$$\frac{\partial FDC}{\partial \sigma} + \frac{\partial TC}{\partial \sigma} \overset{!}{=} 0 \Leftrightarrow \frac{\partial FDC}{\partial \sigma} - \gamma V_0 \overset{!}{=} 0 \Leftrightarrow \frac{\frac{\partial FDC}{\partial \sigma}}{V_0} \overset{!}{=} \gamma \tag{10}$$

In our empirical study, we use the minimum firm-specific value of $\frac{\partial FDC}{\partial \sigma}$ in our sample ("marginal utility of the marginal hedging company") as a proxy for γ, as this value indicates at which transaction cost level hedging is still profitable.

The second-order condition for a minimum of total costs is met, which can be easily seen by taking a look at Equation (7). As the cumulative standard normal distribution function $\phi(x)$ is convex for all x smaller than zero, the sum of FDC and transactions costs is convex in σ as a sum of two convex functions, if

$$\frac{\ln\left(\frac{D}{V_0}\right) - r_f - \frac{1}{2}\sigma^{*2}}{\sigma^*} < 0 \Leftrightarrow D < V_0 e^{r_f + \frac{1}{2}\sigma^{*2}}, \tag{11}$$

which does not imply further restrictions as we already restricted D to be less than $V_0 e^{r_f - \frac{1}{2}\sigma^2} < V_0 e^{r_f + \frac{1}{2}\sigma^2}$ (cf. Appendix A). Hence, σ^* indeed minimizes the sum of *ex-ante* expected FDC and transaction costs.

As the parameter σ represents the asset volatility of the unhedged company and as the optimal level of volatility after hedging is given by σ^*, we can now define the firms' optimal hedge ratios in equilibrium as

$$H_j^* := \frac{\sigma_j - \sigma_j^*}{\sigma_j}. \tag{12}$$

The optimal hedge ratio of the firm is defined as the optimal volatility reduction that satisfies the first-order condition (10) as a percentage of the volatility before hedging. We state the results of this section in the following proposition which lays the basis for our discussion of its testable empirical implications later on.

Proposition. *In the hedging equilibrium, each firm $j = 1, \dots, n$ chooses its optimal hedge ratio H_j^*, so that the sum of* ex-ante *expected FDC and transaction costs is minimized. For a given set of firm-specific parameters $\left(\frac{D_j^*}{V_{0_j}}, PD_j^*, \eta_j^*\right)$ and a non-firm-specific transaction cost parameter γ, there is a unique set of optimal hedge ratios H_j^*. The cross-sectional variation in the firms' hedging behavior can be attributed to differences in the marginal benefits of hedging $\frac{\partial FDC}{\partial \sigma}$, which result from differences in the firm-specific parameters $\left(\frac{D_j^*}{V_{0_j}}, PD_j^*, \eta_j^*\right)$.*

We illustrate the empirical implications of the model—with the help of a numerical example—on the basis of our empirical dataset in Appendix B. However, it is already clear that we aim at explaining the cross-sectional differences in the observed hedging behavior in our sample by the differences in H_j^*, which will be our leading explanatory variable (besides the absolute amount of FDC). H_j^* can be interpreted as the optimal relative (percentage) volatility reduction that minimizes FDC and that combines a set of empirically observable company parameters in a theoretically rigid approach.

3 | EMPIRICAL ANALYSIS

3.1 | Data description and methodology

The dataset is obtained in an anonymized form from a major German bank in line with the rules of banking secrecy. In particular, all company names were erased beforehand. The bank has been in the corporate lending business for decades and is considered systemically relevant for the banking system. Within its internal organization, specialized departments are dedicated to sell all types of derivatives to its corporate clients.

The data contains all the OTC derivative contracts the bank entered with about 500 non-financial, non-public sector counterparties at year-end 2014 and 2015. The dataset includes detailed counterparty information such as legal entity identifier, client group identifier (for client groups consisting of more than one legal entity, i.e. typically one parent company with more than one subsidiary), industry code, current counterparty credit rating and corresponding Basel II PD, the precise product type, and both the current fair value and the nominal amount of the contract. The interest rate risk-related product types included in our sample are interest rate swaps, forward deals as well as caps and floors. The currency risk-related products contain FX swaps, cross-currency swaps, and FX options in about 20 currencies.

The sample does not include exchange-traded products as these derivatives are not bilateral with the bank being the contractual counterparty.

The so-called Basel II PDs are the bank's internal PD estimates, which are used for both bank internal processes like loan approval and margin calculation, but also for the purpose of calculating regulatory capital requirements. The PD estimation is based on a quantitative logit model, which is calibrated to the actual default time series observed within the banking group by means of maximum likelihood estimation and which has been granted a supervisory permission as an IRBA (internal ratings-based approach) model under the Basel II regulation. See, for example, the overview in Engelmann and Rauhmeier (2006) for this typical type of Basel II rating models.[4] The logit model makes use of the firms' equity/total assets ratios, interest coverage ratios, and liquidity ratios, but also employs some other balance sheet and cash flow figures, which constitute the individually transformed input variables and which are then combined within a non-linear function. Hence, the [0;1]-scaled PD function that contains all the balance-sheet data relevant to predict corporate default risk seems to be the natural starting point to estimate the firms' *ex-ante* financial distress costs.

The German market for OTC derivative sales to corporates has been subject to further regulation during recent years (e.g. through the new EU directives EMIR and MiFID II). However, there were no external restrictions that limit the banks' contractual freedom and competition between banks has been close. As we are not aware of any particular internal restrictions either (e.g. bank internal rules that would require a certain hedging policy if a downgrade crosses a rating class border or which are related to its lending standards), we are convinced that the observed contracts are the outcome of a primarily demand-driven process of contract conclusions.

We remove counterparties with missing information, natural persons, and public-private partnerships and limit our analysis to non-defaulted firms with an annual turnover between EUR 5 million and EUR 1 billion as the bank uses different risk management and client approaches for very small and large firms. Hence, our typical sample firm is a German middle-market corporate ("Mittelstand") who has its shares not listed on a stock exchange, so that we cannot measure the hedging benefit on shareholders' equity directly like, for example, in Allayannis and Weston (2001). Moreover, most of these firms rely on bank financing and private debt rather than on issuing tradable bonds, which is in line with the observation that they are not externally rated by the international rating agencies and that their financial statements are prepared according to local Generally Accepted Accounting Principles (GAAP) and not according to International Financial Reporting Standards (IFRS). Many firms in the sample produce goods for worldwide export, so that they need to manage their FX exposure from future revenues in various foreign currencies, actually more than 20 in the sample. However, unlike the sample firms analyzed by Allayannis, Ihrig, and Weston (2001) or by Bartram, Brown, and Minton (2010), they usually do not represent truly multinational corporates in the sense that they run production facilities across international subsidiaries and can thereby apply an arsenal of non-financial hedging instruments. Since our sample firms are on average much smaller and since they form a homogeneous group insofar as they have their production facilities mainly concentrated within Germany or countries of the Eurozone, we think that they will not greatly differ in their use of alternative FX risk management tools, like operational hedging, pass-through or foreign-currency denominated debt. Hence, although we do not have data on these potential other hedging instruments, we think that the derivative use we can observe in the bank data is a very good proxy for the sample firms' overall hedging approach.

In examining the relation between hedging and FDC we estimate the linear regression model

$$y_{i,t} = X_{i,t}\beta + \alpha_i + \gamma_t + \epsilon_{i,t}, \tag{13}$$

where $y_{i,t}$ is the hedge proxy variable and $X_{i,t}$ the design matrix whose rows correspond to the independent variables. α_i denote the industry fixed effects, γ_t the time fixed effects, and $\epsilon_{i,t}$ the error term.

[4] Altman and Sabato (2007) demonstrate the method focusing on US SMEs, while Grunert, Norden, and Weber (2005) use German bank data.

The approach taken is commonly based on linearly regressing a binary variable for the hedger/nonhedger characteristic of the firm on a set of pre-specified explanatory variables. Instead of using a binary regression, other papers (see e.g. Allayannis et al., 2001 and Graham & Rogers, 2002) have used a metric variable for the hedge ratio that is based on mandatory accounting disclosures of derivative use.

We construct three variables as hedge ratio proxies for each firm, namely the sum of all notional values of the derivative contracts divided by (a) its book value of total assets and (b) its total debt. The third hedge ratio proxy (c) is constructed as the sum of all fair values of the derivative contracts divided by the firm's book value of total assets. While we use (a) as our main hedge proxy, we introduce (b) and (c) in the robustness section. A potential disadvantage of aggregating nominal values as a proxy for derivative use arises from neglecting other characteristics of the contracts (e.g. different maturities, long/short positions, etc.). In fact, we are in the lucky position of having access to the detailed single-contract data of all the derivatives the firms have with the particular bank at year-end. But, since we cannot distinguish between differences in the firm's overall open position that underlies the hedging contract at the point in time it was closed, it does not make sense to net between long/short resp. buy/sell positions. Another similar justification for aggregating nominals is given by Carroll et al. (2017), who refer to Hentschel and Kothari (2001): Although one would expect financial firms to hold offsetting positions to run a 'balanced book', non-financial firms have no obvious reason to hold offsetting derivatives positions. So we simply chose to interpret an additional EUR of the aggregated notional amount as an indicator of more hedging activity. Other existing studies suggest using a dummy variable indicating the use of derivatives (e.g. Bartram, 2019) as an alternative measure. Unfortunately, this approach is not applicable in this study since our dataset comprises only companies involved in hedging activities. However, the use of aggregated nominal values is commonly used in many other recent studies (see e.g. Allayannis et al., 2001; Borokhovich, Brunarski, Crutchley, & Simkins, 2004; Gay & Nam, 1998; Graham & Rogers, 2002; Hentschel & Kothari, 2001; Howton & Perfect, 1998; Lel, 2012) and we regard it as the best alternative for our dataset.

Due to the nature of our sample, we solely study firms that are involved in hedging activities, which may introduce a self-selection bias. This potential issue could be bypassed by adding firms to the sample which are not involved in hedging activities and using a Tobit regression instead of ordinary least squares (OLS) to account for the introduced zeros in the dependent variable. For example, Guay and Kothari (2003) also report regressions of hedging activity on proxies for hedging incentives based on a sample of firms using derivatives. In untabulated results, their results are similar for a Tobit specification that included non-derivatives users. Besides sample selection biases, Bartram, Brown, and Conrad (2011) also discuss other empirical challenges such as endogeneity and omitted variables. In an attempt to mitigate these concerns, they use a matching method that controls for the differences in the likelihood of using derivatives. By this, they attempt to find "similar" firms, where to the extent possible the "similar" firm differs only in its choice not to use derivatives. Unfortunately, we cannot conduct a comparable analysis using our data, since a large sample of non-derivative users comparable to ours is required to obtain meaningful matches.

The book value of total assets is our main proxy for company size. Besides size, we include profitability, short-term liquidity, interest coverage ratio, and debt ratio as commonly used control variables in our regression model. These variables were included in the bank's datafile and were *inter alia* used to produce the internal rating valid at year-end, which is also used for the regulatory capital calculation under the Basel II internal ratings-based (IRB) approach. See Table 1 for a detailed overview. Descriptive statistics on the dataset, winsorized at 1% and 99%, are shown in Table 2.

It is commonly argued that firms with higher debt ratios, lower interest coverage, lower profitability, and less liquidity are more likely to use derivatives. Moreover, bankruptcy costs are typically assumed to be less than proportional to firm size, hence smaller firms should be more likely to hedge (Gruber & Warner, 1977). In that sense, these variables can be interpreted as traditional proxy variables for FDC. Empirical evidence on international datasets, which also include observations from Germany, however, has up to now found only mixed support for these hypotheses (see e.g. again Bartram et al. (2009)). The corresponding part of the correlation matrix for our dataset in Appendix C (see Table C.1 in Appendix C) is in line with this literature and supports all of these predictions, since all the correlations

TABLE 1 Variable definitions

Variable	Definition
Dependent variables	
Notionals	Sum of gross notional values of derivative contracts held by the company over book value of total assets.
MV	Sum of absolute fair values of derivative contracts held by the company over book value of total assets.
$\text{Notionals}_{\text{Debt}}$	Sum of gross notional values of derivative contracts held by the company over book value of debt.
Independent variables	
FDC	Expected absolute financial distress costs as constructed in Section 2.
H	Theoretical hedge ratio comprising marginal benefits of FDC reduction through hedging as constructed in Section 2.
Debt ratio	Book value of liabilities over total assets.
Interest coverage ratio	Operating income over interest expenses.
Profitability	Operating income over sales.
Short-term liquidity	Cash and cash equivalents over book value of liabilities.
Size	The natural logarithm of book value of total assets.

Notes: This table shows the definitions of the variables used throughout this study. Independent variables are constructed by balance sheet data used by the bank to obtain the probabilities of default according to its approved regulatory model under the Basel II internal ratings-based approach.

TABLE 2 Descriptive statistics

	Min	Mean	Max	SD
Dependent variables				
Notionals	0.0025	0.0978	0.7222	0.1202
MV	0.0000	0.0034	0.0276	0.0051
$\text{Notionals}_{\text{Debt}}$	0.0042	0.1540	1.1480	0.1936
Independent variables				
FDC	293.75	10843.04	54822.34	12033.89
H	0.2578	0.4060	0.6020	0.0697
Debt ratio	0.2182	0.6722	0.9680	0.1554
Interest coverage ratio	−5.8189	6.8798	56.9224	10.9794
Profitability	−0.0318	0.0423	0.1750	0.0419
Short-term liquidity	0.0012	0.1392	1.5209	0.2341
Size	15.6570	18.1677	20.1976	1.1577

Notes: This table shows the descriptive statistics of the dataset. Notionals respectively $\text{Notionals}_{\text{Debt}}$ is the sum of gross notional values of derivative contracts held by the company over the book value of total assets respectively liabilities. MV is the sum of absolute fair values of derivative contracts held by the company over the book value of total assets. FDC is the absolute amount of expected financial distress costs and H the theoretical hedge ratio comprising marginal benefits of FDC reduction through hedging as constructed in Section 2. Debt ratio is defined as book value of liabilities over total assets. Interest coverage ratio is calculated as operating income over interest expenses and Profitability as operating income over sales. Short-term liquidity denotes cash and cash equivalents over book value of liabilities. Size is measured as the natural logarithm of the book value of total assets.

with the observed derivative use (variables named Notionals and MV) have the hypothesized signs, albeit some are just above the 10% significance level.

For the variable H, which is the optimal hedge ratio we predict on the basis of the marginal FDC, we obtain highly significant negative correlations with interest coverage, profitability, and short-term liquidity and a positive correlation with leverage, which is plausible, as it indicates that our new explanatory variable H is quite in line with the predictions for the commonly applied traditional proxy variables concerning observed hedge ratios. It should be noted that a similar interpretation of the "correct" sign for the correlation coefficients between the absolute FDC variable and the control variables is not valid. The reason for this is that we estimate the absolute FDC as a fraction of firm value in case of bankruptcy, which by construction leads to a high correlation between firm size and the absolute amount of FDC. Hence, the interpretation of the univariate effects is misleading here.

Our final sample consists of 189 medium-sized firms giving us a representative sample of hedging in the German middle-market corporates ("Mittelstand"). Table D.1 in Appendix D shows the industry distribution of the dataset. Due to the size of the companies and their relationship with the major bank, we are likely observing that the vast majority of the firms' hedging activity is channeled through this bank. Machauer and Weber (2000) provide more insights into the German bank/firm relationship and Harhoff and Körting (1998) find most German small and medium-sized companies trade with less than two banks. However, as we cannot ensure that other hedging activities take place, we consider the hedge ratio as a random variable that asymptotically approaches the real (unobservable) hedge ratio with decreasing firm size. Therefore using company size as a control variable in the empirical analysis is both crucial for us and common in previous studies.

3.2 | Absolute FDC and hedging

We begin by testing whether there is a positive relationship between the absolute amount of expected FDC and the observed hedge ratios. To reiterate, the absolute amount of expected FDC is defined as a fraction of an asset-or-nothing put option. Table 3 shows the result of the estimated regression model (13) of the absolute FDC on the scaled sum of notional values of derivative contracts held by each company, considering control variables and both industry and time fixed effects.

Strikingly, the size of a company, measured by the natural logarithm of the book value of total assets, significantly negatively influences the observed hedge ratios. Several explanations come to mind with regard to this finding, especially as it differs from what Graham and Rogers (2002) document. We already mentioned earlier that the probability that a firm engages in derivatives business with more than one bank increases with firm size (Harhoff & Körting, 1998; Ongena & Smith, 2000). Hence, there is an increased probability of missing notional values of derivative contracts for larger companies due to contracts with other banks. Second, one could think of the simple mathematical explanation that, as the observed hedge ratios are scaled by total assets, an enlargement of the denominator can lead to lower hedge ratios if they do not increase proportionally.

Besides the size variable, the only other variable with significant explanatory power in both specifications is the absolute amount of FDC. Its coefficient is significantly positive at the 1% confidence level with a magnitude of 2.9008. Including industry and time fixed effects, this value increases to 2.9132. This indicates that German middle-market companies indeed hedge in order to avoid *ex-ante* expected FDC: The higher the absolute FDC, the greater is the incentive to reduce a portion of firm value volatility by using derivatives.

Regarding the remaining control variables, we cannot observe significant links to the dependent variable. This is surprising as these variables are commonly used proxies for hedging incentives such as expected financial distress. However, one evident reason for this is that the FDC variable already explains the fraction of the observed hedge ratio variations rooted in expected FDC. Obviously, our direct estimation approach yields better empirical results than the use of the traditional proxy variables.

TABLE 3 Regression of hedging extent on hedging incentives including the absolute amount of expected FDC

Dependent variable	Notionals	
Independent variables		
FDC (in million)	2.9008***	2.9132***
	(3.321)	(3.313)
Debt ratio	0.0485	0.0426
	(0.991)	(0.837)
Interest coverage ratio	0.0002	0.0002
	(0.384)	(0.360)
Profitability	0.0229	0.0190
	(0.104)	(0.086)
Short-term liquidity	−0.0015	0.0060
	(−0.071)	(0.246)
Size	−0.0739***	−0.0742***
	(−5.571)	(−5.625)
Intercept	1.3753***	
	(6.261)	
Fixed effects	No	Yes
Adj. R^2	0.2458	0.2348
Observations	321	321

Notes: This table displays the results of the estimated model $y_{i,t} = X_{i,t}\beta + \alpha_i + \gamma_t + \epsilon_{i,t}$, where $X_{i,t}$ denotes the design matrix whose rows correspond to the independent variables, α_i denote the industry fixed effects, γ_t the time fixed effects, and $\epsilon_{i,t}$ the error terms. Below the coefficients the robust t-statistics are given in parentheses. Notionals is the sum of gross notional values of derivative contracts held by the company over book value of total assets. FDC is the absolute amount of expected financial distress costs as constructed in Section 2. Debt ratio is defined as book value of liabilities over total assets. Interest coverage ratio is calculated as operating income over interest expenses and Profitability as operating income over sales. Short-term liquidity denotes cash and cash equivalents over book value of liabilities. Size is measured as the natural logarithm of the book value of total assets. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Regarding our results, we recognize the issue of endogeneity to which empirical studies of corporate hedging are generally prone (see Aretz & Bartram, 2010). Our approach to tackle this challenge is to treat the underlying FDC function as exogenous, insofar as it is designed to measure differences across firms that result from their operating business models when it comes to a situation of financial distress. This FDC function forms the common basis for both the company's hedging and leverage decisions in our modeling approach and is estimated from empirically observable variables.

3.3 | Marginal FDC benefits and hedging

We repeat the previous regression model estimation but replace the absolute amount of FDC with the theoretically optimal hedge ratio H estimated from marginal FDC reduction benefits as an explanatory variable. To reiterate, H results from trading off expected FDC with the transaction costs of hedging these.

H can be interpreted as another perspective on FDC incentives to hedge. While the significantly positive coefficient for FDC in Table 3 implies a higher hedging extent for firms facing higher expected FDC, a significantly positive coefficient here would indicate that the cross-sectional differences between the empirical hedge ratios can be explained by

TABLE 4 Regression of hedging extent on hedging incentives including the marginal benefits of FDC reduction

Dependent variable	Notionals	
Independent variables		
H	0.4443**	0.5033**
	(2.222)	(2.361)
Debt ratio	−0.0915	−0.1105*
	(−1.626)	(−1.835)
Interest coverage ratio	0.0001	0.0002
	(0.216)	(0.347)
Profitability	0.1606	0.1734
	(0.702)	(0.753)
Short-term liquidity	−0.0023	0.0080
	(−0.106)	(0.313)
Size	−0.0480***	−0.0484***
	(−7.398)	(−7.343)
Intercept	0.8460***	
	(7.055)	
Fixed effects	No	Yes
Adj. R^2	0.2470	0.2419
Observations	321	321

Notes: This table displays the results of the estimated model $y_{i,t} = X_{i,t}\beta + \alpha_i + \gamma_t + \epsilon_{i,t}$, where $X_{i,t}$ denotes the design matrix whose rows correspond to the independent variables, α_i denote the industry fixed effects, γ_t the time fixed effects, and $\epsilon_{i,t}$ the error terms. Below the coefficients the robust *t*-statistics are given in parentheses. Notionals is the sum of gross notional values of derivative contracts held by the company over book value of total assets. H is the theoretically optimal hedge ratio estimated from marginal FDC benefits as explained in Section 2. Debt ratio is defined as book value of liabilities over total assets. Interest coverage ratio is calculated as operating income over interest expenses and Profitability as operating income over sales. Short-term liquidity denotes cash and cash equivalents over book value of liabilities. Size is measured as the natural logarithm of the book value of total assets. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

firm-specific, marginal benefits of FDC reduction. Albeit we expect a positive coefficient for the hedge ratio variable H, our expectation about deviations in the magnitude and significance of its coefficient compared to the coefficient of the absolute FDC variable is ambiguous. By construction, H comprises information about both the absolute height of FDC and the marginal benefits of hedging these costs. Hence, we believe that the model estimation will result in a higher regression coefficient for H than FDC. On the other hand, a decrease in the coefficient might indicate a superior role of the absolute expected FDC height in the hedging decision process.

A similar pictures emerges when comparing the results in Table 4 to those obtained in the previous regression (see Table 3). The marginal FDC variable H possesses significant explanatory power in both specifications. The coefficient of H is significantly positive at the 5% confidence level with magnitudes of 0.44 and 0.50 respectively. This finding is in line with our expectations. The economic impact of our results is quite pronounced. A one unit increase in H (FDC) FDC corresponds to a 0.50 (2.91) unit increase in the absolute hedge ratios. Thus companies on average compensate for higher bankruptcy costs by a steep increase in their hedging activities. This magnitude can be explained by the relatively low absolute FDC in our sample as well as the practical implementation costs of higher hedging activity.

TABLE 5 Regression of hedging extent on hedging incentives for different subsamples

Dependent variable	Notionals			
Sample	≤ 75% quantile(Size)		≤ 50% quantile(Size)	
Independent variables				
FDC (in million)	5.7843*		19.7861*	
	(1.936)		(1.674)	
H		0.6190**		0.8816**
		(2.545)		(2.527)
Debt ratio	0.0874	−0.1194	0.2053*	−0.0804
	(1.143)	(−1.576)	(1.858)	(−0.724)
Interest coverage ratio	0.0005	0.0005	0.0011	0.0014
	(0.561)	(0.549)	(0.748)	(0.904)
Profitability	−0.0090	0.2228	−0.2073	0.1142
	(−0.035)	(0.837)	(−0.431)	(0.235)
Short-term liquidity	0.0131	0.0002	0.0487	0.0494
	(0.393)	(0.005)	(0.572)	(0.647)
Size	−0.0869***	−0.0634***	−0.1288***	−0.0890***
	(−4.369)	(−6.080)	(−3.557)	(−4.693)
Fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.1853	0.2193	0.1312	0.1843
Observations	241	241	161	161

Notes: This table displays the results for two subsamples, namely by excluding the 25% respectively 50% largest companies in the sample. The estimated model is $y_{i,t} = X_{i,t}\beta + \alpha_i + \gamma_t + \epsilon_{i,t}$, where $X_{i,t}$ denotes the design matrix whose rows correspond to the independent variables, α_i denote the industry fixed effects, γ_t the time fixed effects, and $\epsilon_{i,t}$ the error terms. Below the coefficients the robust t-statistics are given in parentheses. Notionals is the sum of gross notional values of derivative contracts held by the company over book value of total assets. FDC is the absolute amount of expected financial distress costs and H the theoretical hedge ratio comprising marginal benefits of FDC reduction through hedging as constructed in Section 2. Debt ratio is defined as book value of liabilities over total assets. Interest coverage ratio is calculated as operating income over interest expenses and Profitability as operating income over sales. Short-term liquidity denotes cash and cash equivalents over book value of liabilities. Size is measured as the natural logarithm of the book value of total assets. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

3.4 | Robustness checks

3.4.1 | Extent of derivative use and number of banking relationships

In the attempt to control for the case that larger firms are more likely to possess derivative contracts whose notional values are not included in the dataset, we gradually downsize the dataset with respect to the companies' size and rerun the conducted analysis. More specifically, we build two subsamples based on dismissing (a) the largest 25% and (b) the largest 50% of the firms. We expect both the coefficients of the FDC variables and their significance to increase. The results are documented in Table 5.

In line with expectations, both the FDC and the H coefficient increase each time a smaller subsample is taken into consideration. While for H the coefficient almost doubled compared to the main specification, the FDC coefficient jumps from a magnitude of 2.9132 to 19.7861 when only considering companies having a size below the median firm size of the sample. However, only the coefficient of H is becoming slightly more significant. The FDC coefficient, on the

TABLE 6 Regression of alternative proxies of hedging extent on hedging incentives

Dependent variable	$\text{Notionals}_{\text{Debt}}$		MV	
Independent variables				
FDC (in million)	3.2730**		0.1254***	
	(2.407)		(3.055)	
H		0.5878*		0.0169**
		(1.788)		(2.003)
Debt ratio	−0.1923**	−0.3691***	0.0025	−0.0031
	(−2.124)	(−3.721)	(1.003)	(−1.128)
Interest coverage ratio	−0.0003	−0.0002	0.0000	0.0000
	(−0.269)	(−0.235)	(−1.375)	(−1.298)
Profitability	−0.1110	0.0702	0.0045	0.0095
	(−0.270)	(0.166)	(0.393)	(0.802)
Short-term liquidity	0.0989	0.1016	0.0014	0.0015
	(1.383)	(1.388)	(1.256)	(1.179)
Size	−0.1034***	−0.0743***	−0.0023***	−0.0013***
	(−5.200)	(−7.191)	(−4.300)	(−4.138)
Fixed effects	Yes	Yes	Yes	Yes
Adj. R^2	0.2328	0.2376	0.0988	0.0925
Observations	321	321	321	321

Notes: This table displays the results for two alternative proxies of hedging extent. The estimated model is $y_{i,t} = X_{i,t}\beta + \alpha_i + \gamma_t + \epsilon_{i,t}$, where $X_{i,t}$ denotes the design matrix whose rows correspond to the independent variables, α_i denote the industry fixed effects, γ_t the time fixed effects, and $\epsilon_{i,t}$ the error terms. Below the coefficients the robust t-statistics are given in parentheses. Notionals_{Debt} is the sum of gross notional values of derivative contracts held by the company over book value of liabilities and MV is the sum of absolute fair values of derivative contracts held by the company over book value of total assets. FDC is the absolute amount of expected financial distress costs and H the theoretical hedge ratio comprising marginal benefits of FDC reduction through hedging as constructed in Section 2. Debt ratio is defined as book value of liabilities over total assets. Interest coverage ratio is calculated as operating income over interest expenses and Profitability as operating income over sales. Short-term liquidity denotes cash and cash equivalents over book value of liabilities. Size is measured as the natural logarithm of the book value of total assets. Significance levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

other hand, is less significant for the two subsamples than for the full sample. We believe that this finding is rooted in the relation between the size of a company and our construction of the expected FDC. Our FDC function is defined as a fraction of firm value (see Equation (5)) in the case of bankruptcy. By gradually downsizing the sample with respect to company size, we not only control particularly for size, but also for the absolute amount of FDC. Hence, both size and FDC lose some significance following this procedure, whereas H does not.

3.4.2 | Different measures of the extent of derivative use

So far, we scaled the sum of notional values of derivative contracts by the book value of total assets for each company. Commonly, the amount of debt is used alternatively for scaling the notional values to construct a measure of the extent of derivative use (Graham & Rogers, 2002). Hence, we replace the dependent variable used in the main analysis by one scaled by debt.

This specification can be interpreted as a measure for hedging per dollar of debt. As the left columns in Table 6 show, we obtain similar results to the previously conducted analysis. In this case though, the coefficients of the marginal and absolute FDC variables are significant at the 10% and 5% levels, respectively. Nonetheless, the debt ratio again seems to negatively influence the observed hedge ratios. Graham and Rogers (2002) use the amount of debt as a measure of financial distress and find their results to be robust against this alternative measure of hedging extent. We argue that this specification induces a negative coefficient on the debt ratio because debt is in the denominator of the dependent variable. The correlation matrix C.1 in Appendix C fosters this impression as Notionals $_{\text{Debt}}$ is the only dependent variable being negatively correlated to the debt ratio.

As a third proxy of a firm's hedging extent, we utilize the fair values of the derivative contracts. They specify the amount that the contract holder would receive or pay to liquidate these contracts and have also been utilized as proxies for derivative use in earlier studies (see, e.g., Berkman & Bradbury, 1996; Choi, Mao, & Upadhyay, 2013; Spanò, 2007). A serious disadvantage of using fair values compared to notional values as a hedging proxy is their dependence on the price movements of the corresponding underlying. For example, many fair values of derivative contracts are zero at origination, although their hedged notional values might be large. In our sample though, derivative contracts are already held for 2.5 years on average. Thus, we believe that the sum of the absolute fair values of derivative contracts serves as a suitable alternative to test our hypothesis. The correlation between the constructed hedge proxies based on fair values respectively notional values amounts to 0.642 (see Table C.1 in Appendix C). Table 6 summarizes the results. They are similar to those obtained in the main specifications. Both the coefficient of the marginal and absolute FDC variables are significant at the 5% and 1% levels, respectively, supporting our hypothesis that firms hedge in order to avoid FDC.

4 | CONCLUSION

Exploring if firms hedge in order to avoid *ex-ante* expected FDC, we expand a Merton (1974) framework to estimate FDC as a fraction of an asset-or-nothing put option. Our empirical FDC estimates are based on information about the firms' regulatory "Basel II" PDs, which are available at bank level, as well as on publicly accessible accounting figures. Assuming that firms choose their debt levels optimally, we determine the firm-specific financial distress cost parameters in a trade-off between FDC and tax savings. The resulting absolute amount of firm-specific FDC is our first novel explanatory variable, which is assumed to be positively correlated with the observed hedging activity. We then introduce a second trade-off between FDC and transaction costs to calculate optimal hedge ratios. We expect these optimal hedge ratios, which result from the marginal FDC benefits in equilibrium and which are our second novel explanatory variable, to be accompanied by higher observed hedge ratios, too.

Testing our model empirically, we obtain granular data from a major bank. The dataset contains all OTC derivatives the bank entered with about 189 middle-market counterparties (non-financial, non-public sector) at fiscal year-end 2014 and 2015. Regressing our FDC variables on the observed hedge ratios, we find a significantly positive relation when considering several control variables and fixed effects. Although it is quite probable that most firms in our dataset mainly trade derivatives with only a very small number of banks, we admit that the observed hedge ratios might not cover the full extent of derivative use of the considered companies. Since larger firms are more likely to possess derivative contracts whose notional values are not included in the dataset, we gradually downsize the dataset with respect to the companies' size in the robustness section. In line with our expectations, the magnitude of the coefficients for both FDC variables increases. Furthermore, our results are robust to different constructions of the empirical hedge ratio and different choice of model parameters.

Our contribution is a novel measure of firm-specific *ex-ante* costs of financial distress based on an option-theoretical approach, which we then extend to an equilibrium setting. Moreover, our empirical analysis differs from previously used datasets and enriches the literature by the perspective of a financial intermediary on the corporate hedging decision. We are able to support the hypothesis that firms hedge in order to avoid *ex-ante* expected financial distress costs.

Concerning implications of our findings for corporate policy as well as for banks' derivative sales policies, we think that a quantitative analysis of the FDC impact should become a more explicit part of firms' hedging decisions. For the German middle-market companies we have focused on in this paper, such an analysis should expediently be linked to the annual Basel II rating process, whose main outcome is a forward-looking one-year default probability. In this context, our modeling approach to estimate *ex-ante* expected FDC could be integrated for benchmarking purposes. From a financial intermediate's perspective, such quantitative information should be embraced as a new anchor point for offering customized consulting and marketing activities in financial derivatives.

From a research point of view, currently only very little seems to be known about the role of the sell-side for corporate derivatives use. In order to gain more insight about the policies of the different sell-side market participants and their views on the corporate decision process, more survey work seems necessary in a first step.

The partial equilibrium two-stage estimation approach presented in this paper is applicable in future research projects or the above mentioned quantitative business analyses whenever data about the firms' debt-equity ratio and a corresponding PD proxy variable is available. The PD proxy variable, which we took from our bank dataset as a regulatory Basel II PD, could easily be replaced by mean historical default rates per rating class if a sample of externally rated firms was analyzed. Moreover, such a proxy variable could also be constructed from observed credit spreads, if the firms under analysis have issued bonds, which are traded in a liquid debt market, or if there are even liquid CDS quotes. In order to have a substantial magnitude of FDC in the sample, a natural choice would be the European market for high-yield bond issuers, where both external ratings and credit spreads are available.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are not publicly available as the dataset is proprietary.

CONFLICT OF INTEREST STATEMENT

No conflict of interest has been declared by the authors.

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APPENDIX A: ESTIMATING THE FINANCIAL DISTRESS COST PARAMETER η FROM A CAPITAL STRUCTURE EQUILIBRUM

In order to provide a counterweight to the FDC given by (7), we introduce a corporate tax function. Interest rates are tax-deductible, which provides an incentive for borrowing at the corporate level by generating a tax shield. Taxable income in $t = 1$ stems from operating earnings (EBIT), which go along with an increase (or decrease) in total assets from V_0 to V. It is reduced by multiplying the nominal interest rate $i > 0$, which is assumed to be constant across all firms for the sake of simplicity, times the debt level that is chosen by the company. The corporate tax rate is denoted as $\tau \in]0, 1[$. The resulting tax shield is only valuable in those future states of the world, where the taxable income is not negative anyway. The whole idea of tax shield modeling is to create an analytically tractable counterweight to financial distress costs for the firms' capital structure decision. It is not meant as an analysis to further explore tax reasons for corporate hedging, which we do not regard as relevant under the German tax system. See Graham and Rogers (2002) for such an analysis for the US. The market value of the tax claim in $t = 0$, which is identical with the expected value of the random cash flow in $t = 1$, emerges as

$$T := \tau \int_{V_0+iD}^{\infty} (V - V_0 - iD) f(V, \mu, \sigma) dV. \tag{A.1}$$

The shareholders decide about the optimal debt amount by maximizing the market value of their residual claims in $t = 1$. Since the debtholders are fairly compensated for the default risk, the maximization of shareholder wealth is equivalent to minimizing the sum of the market values of taxes and financial distress costs. This yields the first-order condition

$$\frac{\partial T}{\partial D} + \frac{\partial FDC}{\partial D} \overset{!}{=} 0. \tag{A.2}$$

Applying the product rule to the derivative of the tax function leads to

$$\frac{\partial T}{\partial D} = -\tau i + \tau i F(V_0 + iD, \mu, \sigma) < 0. \tag{A.3}$$

Applying Leibniz' rule, the first partial derivative of Equation (5) with respect to D is given by

$$\frac{\partial FDC}{\partial D} = \eta D f(D, \mu, \sigma) > 0. \tag{A.4}$$

When the firm has chosen its unique optimal debt level $D = D^*$ according to the first-order condition (A.2), the following condition must hold for the financial distress cost parameter η^*:

$$\begin{aligned} -\frac{\partial T}{\partial D} = \frac{\partial FDC}{\partial D} &\Leftrightarrow \tau i - \tau i F(V_0 + iD^*, \mu, \sigma) = \eta^* D^* f(D^*, \mu, \sigma) \\ &\Leftrightarrow \eta^* = \frac{\tau i - \tau i F(V_0 + iD^*, \mu, \sigma)}{D^* f(D^*, \mu, \sigma)}. \end{aligned} \tag{A.5}$$

To ensure the optimal debt level D^* is indeed minimizing the sum between the market values of taxes and financial distress costs, the second order condition needs to be met:

$$\frac{\partial^2 T}{\partial D^2} + \frac{\partial^2 FDC}{\partial D^2} = \tau i^2 f(V_0 + iD, \mu, \sigma) + \eta f(D, \mu, \sigma) + \eta D \frac{\partial}{\partial D} f(D, \mu, \sigma) \overset{!}{>} 0. \tag{A.6}$$

It is sufficient to take the second part of this equation into account, as the second derivation of the tax function $\frac{\partial^2 T}{\partial D^2} = \tau i^2 f(V_0 + iD, \mu, \sigma)$ is greater or equal to zero regardless of the chosen debt level D. Simple mathematical operations show for the second derivation of the financial distress costs function that

$$\begin{aligned} \frac{\partial^2 FDC}{\partial D^2} &= \eta f(D, \mu, \sigma) + \eta D \frac{\partial}{\partial D} f(D, \mu, \sigma) = \frac{\eta}{\sqrt{2\pi}\sigma D} e^{-\frac{(\ln(D)-\mu)^2}{2\sigma^2}} + \eta \left(-\frac{1}{\sqrt{2\pi}\sigma D} e^{-\frac{(\ln(D)-\mu)^2}{2\sigma^2}} - \frac{\ln(D) - \mu}{\sqrt{2\pi}\sigma^3 D} e^{-\frac{(\ln(D)-\mu)^2}{2\sigma^2}} \right) \\ &= \frac{\eta}{\sqrt{2\pi}\sigma^3 D} e^{-\frac{(\ln(D)-\mu)^2}{2\sigma^2}} (\mu - \ln(D)) > 0 \end{aligned} \tag{A.7}$$

if $D < e^{\mu} = V_0 e^{r_f - \frac{1}{2}\sigma^2}$. Thus, if D^* is less than the median of the respective lognormal distribution, in other words if the probability of default of the company is less than at least 50%, D^* is indeed a cost minimum. We summarize these intermediate results in a Lemma:

Lemma. *In the exogenous capital structure equilibrium, each firm $j = 1, \dots, n$ chooses its optimal debt level D_j^*, so that the sum of* ex-ante *expected corporate taxes and financial distress costs is minimized. For any given set of firm-specific distribution parameters (μ_j, σ_j) and of non firm-specific parameters for interest and tax rates, there is a unique set of firm-specific financial distress cost parameters η_j^*, which characterizes this capital structure equilibrium.*

In the empirical part of this study, we set the the total average effective tax rate on company profits to 30%, which comprises both federal tax and municipal tax components (BdF, 2016) and the interest rate i to 1.94% for 2014 and to 1.68% for 2015, which were the effective rates for new loans to non-financial firms granted by German banks in December of the respective year according to Beier and Bade (2017).

APPENDIX B: CONSTRUCTION OF THE FDC VARIABLES

We want to motivate the construction process of the FDC variables with some graphical illustrations. Given the empirical book values of debt and total assets of the 189 firms in our sample and their probabilities of default according to the internal ratings-based approach of the bank, we can numerically solve for the firm value volatility following the Merton (1974) framework (cf. Equation (4)). For example, we pick a random observation from the dataset with book values of debt and totals assets amounting to about EUR 115 million and EUR 228 million respectively, and a probability of default of 0.53%. For this firm one obtains a firm value volatility of about 25.5%.[5] Note that we have set $r_f = 0$ without loss of generality.

We now utilize our FDC model and are able to calculate η_j^* for each firm $j = 1, \dots 189$ following the closed formula (A.5). As shown in Appendix A, this setting (D_j^*, η_j^*) is optimal in the sense of trading off expected financial distress costs and tax savings. Figure B.1 visualizes this choice for the exemplary firm mentioned above.

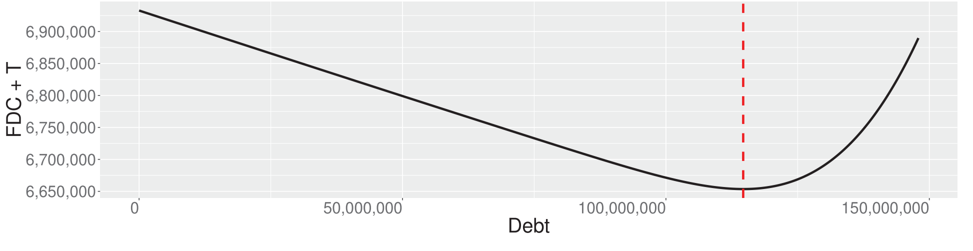

FIGURE B.1 Visualization of the first optimization problem (see Equation (A.2)). The solid black line shows the sum of financial distress costs and taxes in dependence of debt D. The red dotted line shows the optimal amount of debt D^*, given the FDC parameter η^* [Colour figure can be viewed at wileyonlinelibrary.com]

Thereupon, we are able to determine the expected FDC determined by multiplying the FDC parameter η^* with the value of the asset-or-nothing put option (cf. Equation (7)). To prevent firms from fully hedging all of their risk, we introduce transaction costs as described in formula (9). The marginal transaction costs parameter γ is set to 0.4 basis points, which is the minimum firm-specific value of the derivation of the FDC function (cf. Equation (7)) with respect to the firm value volatility. By numerically solving Equation (10), we obtain the optimal firm value volatility σ^* that minimizes the *ex-ante* expected FDC with respect to transaction costs. For the exemplary firm mentioned at the beginning of this section, this optimization is illustrated in Figure B.2.

Finally, we are able to determine the theoretically optimal hedge ratio H^* according to Equation (12) which is driven by the marginal benefits of FDC reduction. Figures B.3 and B.4 show H^* in dependence of the debt ratio and PD. The black points highlight the obtained values H_j^* based on the observations as of 2015 from the dataset.

[5] A direct comparison of this asset volatility with stock price volatilities as a benchmark is not appropriate. The leverage effect that scales up the equity volatility would be counterbalanced by the fact that the middle-market firms in our sample would have relatively large debt market value volatilities due to their lower credit quality typically reflected in a non-investment grade rating. Since there is no marketable debt for these firms, but only bank financing, there are no adequate data that could be used to make such a comparison.

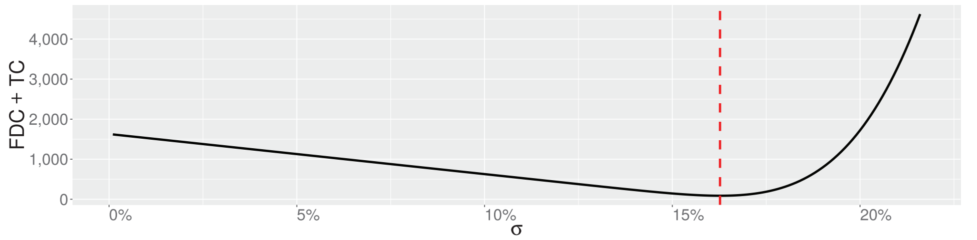

FIGURE B.2 Visualization of the second optimization problem (see Equation (10)). The solid black line shows the sum of financial distress costs and transaction costs in dependence of the firm value volatility σ. The red dotted line shows the optimal firm value volatility σ^* [Colour figure can be viewed at wileyonlinelibrary.com]

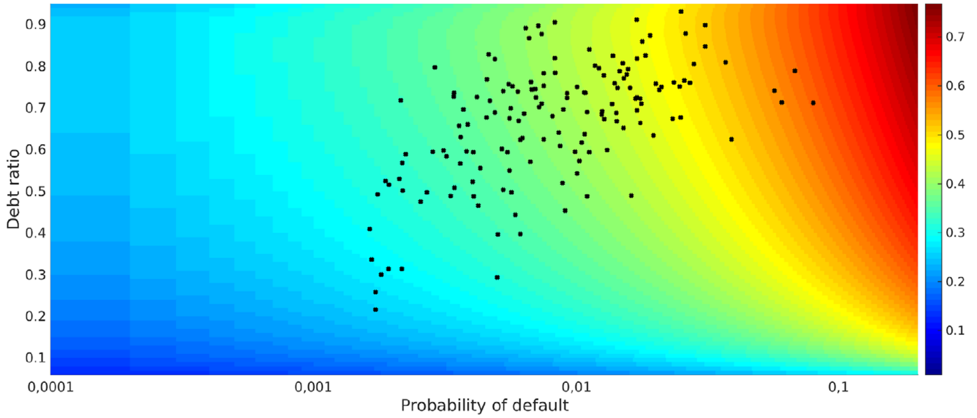

FIGURE B.3 Contour plot of the theoretical hedge ratio H^* in dependence of the debt ratio $\frac{D}{V}$ and probability of default *PD*. The black points highlight the obtained values H_j^* based on the observations as of 2015 from the dataset. Note that the *x*-axis is for the sake of clarity logarithmically scaled [Colour figure can be viewed at wileyonlinelibrary.com]

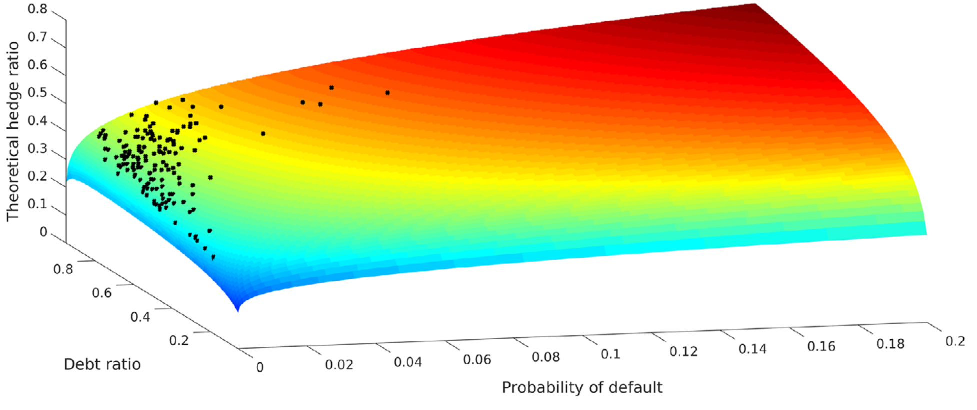

FIGURE B.4 Theoretical hedge ratio H^* in dependence of the debt ratio $\frac{D}{V}$ and probability of default *PD*. The black points highlight the obtained values H_j^* based on the observations as of 2015 from the dataset [Colour figure can be viewed at wileyonlinelibrary.com]

APPENDIX C: CORRELATION MATRIX

TABLE C.1 Correlation matrix

	Notionals	MV	$\text{Notionals}_{\text{Debt}}$	Debt ratio	Interest coverage ratio	Profitability	Short-term liquidity	Size	FDC
MV	0.642***	1							
	(14.960)								
$\text{Notionals}_{\text{Debt}}$	0.915***	0.601***	1						
	(40.516)	(13.417)							
Debt ratio	0.082	0.065	−0.145***	1					
	(1.478)	(1.169)	(−2.617)						
Interest coverage ratio	−0.089	−0.091	0.010	−0.424***	1				
	(−1.590)	(−1.633)	(0.171)	(−8.357)					
Profitability	−0.087	−0.048	−0.039	−0.287***	0.564***	1			
	(−1.556)	(−0.866)	(−0.697)	(−5.348)	(12.205)				
Short-term liquidity	−0.051	−0.022	0.121**	−0.486***	0.499***	0.423***	1		
	(−0.913)	(−0.393)	(2.169)	(−9.927)	(10.281)	(8.331)			
Size	−0.403***	−0.238***	−0.359***	−0.109*	0.146***	−0.016	0.003	1	
	(−7.874)	(−4.378)	(−6.873)	(−1.958)	(2.634)	(−0.289)	(0.047)		
FDC	−0.300***	−0.145***	−0.253***	−0.232***	0.042	0.065	0.019	0.736***	1
	(−5.607)	(−2.616)	(−4.661)	(−4.259)	(0.752)	(1.171)	(0.340)	(19.392)	
H	0.221***	0.190***	0.029	0.653***	−0.487***	−0.469***	−0.457***	−0.147***	−0.113**
	(4.057)	(3.452)	(0.524)	(15.391)	(−9.958)	(−9.491)	(−9.177)	(−2.662)	(−2.035)

Notes: This table shows the Pearson correlation coefficients of the dependent and independent variables. Below the coefficients the *t*-statistics are given in parentheses. Notionals respectively $\text{Notionals}_{\text{Debt}}$ is the sum of gross notional values of derivative contracts held by the company over book value of total assets respectively liabilities. MV is the sum of absolute fair values of derivative contracts held by the company over book value of total assets. Debt ratio is defined as book value of liabilities over total assets. Interest coverage ratio is calculated as operating income over interest expenses and Profitability as operating income over sales. Short-term liquidity denotes cash and cash equivalents over book value of liabilities. Size is measured as the natural logarithm of the book value of total assets. FDC is the absolute amount of expected financial distress costs and H the theoretical hedge ratio comprising marginal benefits of FDC reduction through hedging as constructed in Section 2.

APPENDIX D: INDUSTRY DISTRIBUTION

TABLE D.1 Industry distribution of the dataset

Industry sector	Absolute	Relative (%)
Consumer Non-Durables	62	19.31
Consumer Durables	10	3.12
Manufacturing	97	30.22
Oil, Gas, and Coal	0	0.00
Chemicals	12	3.74
Business Equipment	1	0.31
Telephone and Television	0	0.00
Utilities	2	0.62
Wholesale, Retail, and Some Services	102	31.78
Healthcare, Medical Equipment, and Drugs	0	0.00
Money Finance	0	0.00
Other	35	10.90

Note: This table shows the industry distribution of the dataset. Originally, firms were classified by the German “WZ2008” code, which we mapped to Fama–French 12 industry classes obtained from Kenneth French’s homepage using three cross-walks, namely WZ2008 to ISIC Rev. 4, ISIC Rev. 4 to NAICS 2017, and NAICS 2017 to SIC. We checked each mapping to avoid unreasonable mappings.