The Impact of Default Risk on Equity Returns: Evidence from a Bank-based Financial System

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Abstract

Although default risk primarily is a firm-specific risk factor and thus diversifiable, it is likely that it entails a systematic component as well. In this paper, we examine the impact of default risk on equity returns in Germany over the period 1990-2006. We use an implementation of Merton's option-pricing model for the value of equity to estimate firms' default risk and construct a factor that measures the excess return of firms with low default risk over firms with high default risk.

Since Germany is the prime example of a bank-based financial system, where debt is supposedly a major instrument of corporate governance, we expect that a systematic default risk effect on equity returns should be more pronounced for German rather than U.S. firms.

We find evidence consistent with default risk being a systematic factor priced in capital markets. Further, our analysis shows, that this risk is only barely related to the firm size and market-to-book factor advocated by Fama/French. Our estimates indicate that a higher sensitivity to systematic default risk leads to lower returns. To understand what drives default risk sensitivity, we relate firms' default risk betas to their individual default risk and other control variables like the industry affiliation. It turns out that there is no linear relationship, and the general association between individual default risk and the sensitivity to non-diversifiable market default risk is weak in general.

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1 Introduction

Over the past decades, most empirical asset pricing literature has had only limited success to find systematic factors explaining stock returns. Empirical factors vary across countries and time-periods and often lack a theoretical justification. Surprisingly little attention has been paid on the question, how default risk affects equity returns, and this is the issue addressed in this paper.

Although default risk primarily is a firm-specific risk factor and thus diversifiable, it is likely that it also entails a systematic component. There are at least four arguments why default risk could affect equity returns. First, the arbitrage pricing theory, APT, (Ross (1976)) shows that multiple factors may determine expected returns on equity in equilibrium. Since APT does not imply what these factors are, conclusions could be based on the evidence (empirical stylized facts). Denis and Denis (1995) find evidence that default risk is related to macroeconomic factors, other studies indicate a direct effect of default risk on equity returns in the U.S.[2]

Second, more technically, if a firm is leveraged, equity risk (systematic risk and volatility) and therefore expected returns depend on firms' indebtedness, with a non-stationary relationship between equity volatility and the volatility of firm assets (see Galai and Masulis (1976)). Since default risk is ceteris paribus increasing in leverage, equity returns should be related to default risk. Ferguson and Shockley (2003) show that conducting asset pricing tests on equity prices therefore leads to biased estimates of factor sensitivities, with the bias increasing in a firm's relative leverage and distress risk. Moreover, firm-specific variables that correlate with leverage or default risk will serve as respective instruments, potentially explaining the statistical significance of the size and the book-to-market factor.

Third, changes in the economic environment can lead to cross-sectionally correlated firm and investor behavior, giving rise to non-diversifiable equity return patterns. For example, Fama and French (1996) argue that their SMB and HML factors proxy for financial distress, because if distress risk is cross-sectionally correlated, workers with specialized human capital in distressed firms will avoid to hold stocks subject to default risk, thus requiring a risk premium. Also, if firms' capital structure decisions are driven by some joint factors, changes in firm leverage will be correlated in the cross-section, thereby leading to non-diversifiable stock return patterns related to leverage. There is a lot of corresponding evidence showing that firms are more likely to issue equity in specific market stages, also discussed as the so-called "hot issue markets"

[2] See for example Dichev (1998), Griffin and Lemmon (2002), Vassalou and Xing (2004), Campello and Chen (2005) or Zhang (2006).

and the "market-timing" explanation for capital structure decisions (see e.g. Ritter 1995)

Finally, the modern theory of financial intermediation suggests that in imperfect capital markets with information asymmetries between firm owners, managers, and outside investors, debt can be an efficient way of solving conflicts of interest between these parties (see e.g. Shleifer and Vishny (1997)). Hence, characteristics of debt can directly affect firm performance, and therefore expected equity returns, and this effect may be influenced by the financial system the firms operate in.

In this paper, we examine the impact of default risk on equity returns for listed firms in Germany over the period 1990-2006. Using German data is interesting in the context of default risk, since the German financial system is the prime example of a bank-based financial system, where the role of banks as an active mechanism of corporate governance (in particular through debt financing, equity holdings, and representation in the supervisory board) is significant even for large, exchange listed firms (Gorton and Schmid (2000)). Hence, if the sensitivity of equity returns against a systematic default factor is driven by the relevance and composition of corporate debt, then one should expect that this effect is even more (price) relevant in a bank-based financial system than in the U.S. [3]

Similar to the seminal study by Vassalou and Xing (2004), we avoid using default risk measures based on accounting information, which give rise to problems due to the inherently backward-looking orientation of annual reports, accounting discretion, and the lack of timeliness of information. [4] In contrast, the Merton (1974) model uses the market value of equity and an estimate of the market value of debt to calculate default risk, thus relying on the most frequently available and forward looking information to asses the likelihood that a firm defaults in the future. Furthermore, the Merton (1974) model takes into account the volatility of a firm's assets. Firms with similar leverage can have very different default probabilities due to asset volatility, which is typically not considered by accounting models. Since asset volatility is a key input to the option pricing formula, this constitutes another crucial advantage of our methodology.

The paper is organized as follows. In the next section, we present the methodology used to estimate default risk of firms and to construct the default risk factor used in the subsequent asset pricing tests. Section 3 presents the data and descriptive statistics on the factors used to explain equity returns,

[3] In addition, the German capital market has been barely studied empirically, providing for an excellent replication possibility to validate other empirical results on the impact of default risk on equity returns.

[4] These problems might also explain the contradictory findings in previous studies based on Altman's Z-Score (Altman (1968)), Ohlson's O-Score model (Ohlson (1980)), or bond spreads.

with an emphasis on the distress factor. Section 4 provides the results for the asset pricing tests on the German capital market. Section 5 explores the economics of the systematic default risk factor by examining the determinants of firms' default factor sensitivities. Section 6 concludes.

2 Methodology

2.1 Estimating Firms' Probabilities of Default

The main question of this paper leads to the problem of measuring default risk. Economically, default occurs if the value of a firm's assets is less than the value of debt. The probability of default thus depends on the unobservable firm characteristics (market-value based) leverage, asset value and asset volatility. To use timely and forward-looking information, these characteristics are inferred from daily equity market values, using the relationship postulated by Merton (1974). A firm's equity is viewed as a call option on the firm's assets, where the book value of debt due at time $t = T$ is the strike price, X, and t denotes time. Consequently, if the value of assets is lower than X, the value of equity is zero. We assume that the market value of a firm's assets follows a Geometric Brownian Motion and satisfies the stochastic differential equation:[5]

$$dA_t = \mu_A A_t dt + \sigma_A A_t dW_t \tag{1}$$

where A_t denotes the firm's asset value at time t with an instantaneous drift μ_A, and an instantaneous volatility σ_A. W_t is a standard Wiener process. The equity value E then follows from the Black and Scholes (1973) formula:

$$E_t = A_t \Phi(d_{1,t}) - X e^{-rT} \Phi(d_{2,t}) \tag{2}$$

X describes the strike price of the call, and $\Phi(s)$ denotes the value of the standard normal distribution at s. d_1 and d_2 are given by:

$$d_{1,t} = \frac{ln(\frac{A_t}{X}) + [r + \frac{1}{2}\sigma_A^2]T}{\sigma_A \sqrt{T}} \tag{3}$$

$$d_{2,t} = d_{1,t} - \sigma_A \sqrt{T} \tag{4}$$

In the empirical implementation, the unobservable variables σ_A and A_t can be iteratively calculated for each day in the observation period of our stocks.[6]

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[5] See Vassalou and Xing (2004).

[6] This approach is similar to the one used by Vassalou and Xing (2004) and KMV (see Crosbie and Bohn (2002)).

For each time point t, the preceding 250 trading days are used to estimate σ_E as an *initial guess* for the asset volatility, σ_A. Applying the Black/Scholes formula, we get a series of asset values, A_t. These are in turn used to get another estimate of σ_A. This estimate is used for the next iteration, and the procedure is continued until two consecutive σ_A estimates converge with a tolerance level of $10E-6$. Once the asset volatility has converged (which rarely takes more than just a few iterations), the asset value A_t is calculated, using again equation (2).

A firm's probability of default at day t, PD_t, then follows from

$$PD_t = \text{Prob}(A_{t+T} \leq X|A_t) = \text{Prob}(ln(A_{t+T}) \leq ln(X)|A_t) \tag{5}$$

Using the Geometric Brownian Motion relation for the firm's assets

$$A_{t+T} = A_t \cdot exp\left((\mu_A - \frac{\sigma_A^2}{2})T + \sigma_A\sqrt{T}\epsilon\right) \tag{6}$$

where $\epsilon \sim \mathcal{N}(0,1)$, a logarithmic expression can be derived:

$$ln(A_{t+T}) = ln(A_t) + (\mu_A - \frac{\sigma_A^2}{2})T + \sigma_A\sqrt{T}\epsilon \tag{7}$$

Hence,

$$\begin{aligned} PD_t &= \text{Prob}\left[ln(A_t) + (\mu_A - \frac{\sigma_A^2}{2})T + \sigma_A\sqrt{T}\epsilon - ln(X) \leq 0\right] \\ &= \text{Prob}\left[-\frac{ln(A_t) - ln(X) + (\mu_A - \frac{\sigma_A^2}{2})T}{\sigma_A\sqrt{T}} \geq \epsilon\right] \end{aligned} \tag{8}$$

Thus, the probability of default can be computed by

$$PD_t = \Phi\left(-\frac{ln(\frac{A_t}{X}) + (\mu_A - \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}}\right) \tag{9}$$

or alternatively, one can calculate the distance-to-default (DD) as

$$DD_t = \frac{ln(\frac{A_t}{X}) + (\mu_A - \frac{1}{2}\sigma_A^2)T}{\sigma_A\sqrt{T}} \tag{10}$$

Note that Φ denotes in our model a standard normal distribution function but empirical analysis find better results using a Student's t-distribution function. [7]

The PD measures a firms probability of default at $t = T$ under the real measure, that is, we use μ_A rather than the risk free rate as the drift term. [8]

[7] See Furfine and Rosen (2006).
[8] μ_A is estimated from the time series of asset values and meets the condition $\mu_A = max[r, \hat{\mu}_A]$, to avoid expected returns lower than the risk free rate.

The distance-to-default (DD) tells how many standard deviations the asset value needs to drop to meet the debt value, which triggers default. Hence, a lower DD translates into a higher probability of default, and vice vera. In the following, we use the distance-to default to sort firms on their default risk. This particularly solves the problem, that very frequently observed high values of DD correspond to very low probability of defaults, which might raise numerical issues in calculations.

2.2 Factor Construction and Test Assets

The empirical modeling of our study uses the CAPM, the Fama/French three factor model, and two models that augments the Fama/French systematic factors by one default factor. We construct those default risk factors using two simple approaches. The first approach follows the Fama and French (1993) methodology. More precisely, we create a SIZE list sorted by firm's size, a BM list sorted by book-to-market equity and a distance-to-default (DD) list sorted by the distance-to-default of the individual company. In addition, we divide the three lists into big (B) and small (S) companies, then companies with low (L) and high (H) BM and finally firms with low (l), medium (m) and high (h) distance-to-default. Thus, each firm receives three attributes SIZE/BM/DD. For example a firm can be small with low BM and low distance-to-default which makes it member of the portfolio with the attributes S/L/l. The intersections of the three decomposed lists constitute 12 (2 x 2 x 3) possible portfolios. Therefore we define:

$$
\begin{aligned}
DEF_t = & [R_{S/L/h,t} + ... + R_{B/H/h,t}]/4 - \\
& [R_{S/L/l,t} + ... + R_{B/H/l,t}]/4
\end{aligned}
\tag{11}
$$

Notice that $R_{X/Y/Z,t}$ is the return for the X/Y/Z portfolio at time t, X stands for a SIZE portfolio (S=small, B=big) ,Y denotes a BM portfolio (H=high, L=low) and Z describes a DD portfolio (h=high, m=med, l=low). The second default factor is constructed as proposed by Vassalou and Xing (2004).

$$
\Delta(SV_t) = E_i[1 - PD_{i,t}] - E_i[1 - PD_{i,t-1}] \quad i = 1...N_{C,t} \tag{12}
$$

where $\Delta(SV_t)$ denotes the change of the aggregate survival rate. E_i is the simple average over all $N_{C,t}$ companies included at time t. Note the crucial difference between the default risk factors: While the DEF factor is an excess return similar to HML and SMB, the variant used by Vassalou and Xing (2004) is no return, but rather a measure of the change in aggregate default risk. Most importantly, $\Delta(SV_t)$ is no market price of risk, which renders the use of the traditional time series based asset pricing test (where excess returns of test assets[9] are regressed on the factors) infeasible, since there is no reason to

[9] The different portfolios used to test the models are called test assets.

expect an intercept of zero. Recall that the intercept of such an excess return regression is the measure of systematic returns not explained by the empirical asset pricing model.

The construction of the remaining three factors, the Fama/French factors, namely RMRF (market factor), SMB (small minus big) and HML (high minus low) follows the traditional way. RMRF is expressed by the return of a proxy for the market portfolio that is in Germany the Composite DAX (CDAX) minus the risk free rate, though we cross check all results with a self-constructed value-weighted market factor. The SMB and HML factor are created using the methodology discussed in detail in the Fama and French (1993) paper.

Finally, the test assets used in the asset pricing test are constructed similar to the 12 portfolios described earlier. As proposed by Vassalou and Xing (2004), to capture the three effects with assets providing maximum dispersion regarding the factors, we would like to use a 3 x 3 x 3 form of independent sorts. Unfortunately, the data set of the German stock market does not support enough companies to decompose into 27 portfolios using three dimensions. Thus, we use the smaller set of test assets 2 x 2 x 3. Hence, the SIZE list is divided into two parts, Small(S) and Big(B), the BM list is also divided into two parts, Low(L) and High(H) and finally the DD list is divided into three parts, low DD(l), medium DD(m) and high DD(h). Corresponding portfolio returns are again computed according to Fama and French (1993).

2.3 Econometric Methodology

The objective of the paper is to test whether default risk is systematically priced on the German capital market, and whether HML and SMB proxy for default risk, if these are systematic pricing factors in Germany in the first place. We use the Generalized Method of Moments (GMM) methodology by Hansen (1982) and employ the asymptotically optimal weighting matrix throughout. To allow for comparisons of our results with previous studies, we conduct both a simultaneous time-series and cross-sectional test, and the stochastic-discount-factor test as outlined by Cochrane (2005).

The simultaneous time-series and cross-section test basically estimates portfolio factor sensitivities using times series resgressions and then conducts cross-sectional regressions of portfolio returns on (estimated) factor sensitivities to estimate factor risk premia. Doing this simultaneously in the GMM framework allows to correct inference for the error-in-variables bias inherent in the cross-section regressions.

The stochastic discount factor framework estimates a linear function of the factors, i.e. the pricing kernel, trying to explain which factors help pricing future cashflows of assets. The pricing kernel is the stochastic discount factor that translates future uncertain cashflows (or returns) into today's observed prices. Average prices should be a linear function of covariances between returns and factors. The GMM estimate therefore corresponds to a linear cross-sectional regression of sample average returns on covariances of asset returns with factors across assets. In the appendix, both methods are described and specified in detail.

3 Data and Summary Statistics

Our sample of German listed firms consists of 1110 firms over the period December 1989 - June 2006. Daily price data are from Datastream, whereas yearly book data comes from Worldscope. The German Central Bank (Deutsche Bundesbank) provides the daily time series of the risk free rate, the one-month FIBOR/EURIBOR. All returns are adjusted for capital measures and dividends. [10]

Table 1
Number of Companies per Year

The table reports the number of German companies contained in the sample. A company is only reported if and only if it has at least one non-empty return index per June of the correspondent year τ in Datastream and one book value sequence of the past year $\tau - 1$ in Worldscope.

year	# of companies	year	# of companies
1990	223	1998	397
1991	247	1999	428
1992	256	2000	534
1993	247	2001	587
1994	299	2002	564
1995	294	2003	514
1996	326	2004	506
1997	363	2005	501

We examine only stocks with ordinary common equity and exclude financial firms, similar to Fama and French (1993). [11] Companies are only included into our yearly portfolio constructions and thus into our tests if they have at least one return for June τ and information on total debt, total common equity, preferred stock and deferred taxes in year $\tau - 1$. The resulting number of firms over time is reported in Table 1. Notice that the numbers of companies within this Table are used to compute the Fama/French factors. However, for the

[10] We have spend considerable effort to cross-check and correct the Datastream data for the typical problems of this database, like mistyped values, repeated values for holidays, entered values for already delisted firms etc. For an overview on typical problems associated with Datastream, see Ince and Porter (2006).

[11] ADRs and REITs are not available on the German stock market for our observation period.

calculation of the DEF factor, the sample reduces to a total of 894 companies as the necessary information to estimate distance-to-defaults eliminate more observations.

3.1 Portfolio Returns and Default Risk Characteristics

For descriptive purposes, Table 2 shows the average individual default risk, size and book-to-market ratio for the 2 x 2 x 3 test portfolios. Panel A in Table 2 shows on the left hand side the average firms' market capitalization (of equity) measured in billion Euros, and on the right hand side the average book-to-market ratio. Panel B shows the average distance-to-default of the portfolios, where a high DD corresponds to low default risk and vice versa. Firm size and default risk appear not to be correlated strongly, since the average DD between portfolios with small and big firms barely differ. For example, small firms with high BM in the High DD group have on average a DD of 13.058, while big firms' average distance-to-default with high BM is 12.993.

Table 2
Descriptive Statistics of DD Portfolios

This table shows the average individual default risk, size and book-to-market ratio for the 2 x 2 x 3 test portfolios. The left hand side of Panel A describes the average company size in billions within the portfolio whereas the right hand side illustrates the average company's BM ratios. Panel B presents the mean distance-to-default and its standard deviation of each of the 12 portfolios. The labels of the tables denote the portfolio attributes "SIZE & BM" on the left and "DD" on the upper side.

Panel A: Size and BM within the 12 portfolios

	SIZE			BM		
	LowDD	MedDD	HighDD	LowDD	MedDD	HighDD
Small & LowBM	0.084	0.118	0.144	0.089	0.327	0.322
Small & HighBM	0.083	0.117	0.135	1.382	1.289	1.089
Big & LowBM	0.862	3.673	4.043	0.114	0.316	0.307
Big & HighBM	1.316	2.466	3.862	1.044	0.932	0.871

Panel B: DD and its standard deviation within the 12 portfolios

	DD			STD(DD)		
	LowDD	MedDD	HighDD	LowDD	MedDD	HighDD
Small & LowBM	2.476	6.002	13.641	1.619	2.272	4.557
Small & HighBM	2.604	5.979	12.474	1.637	2.447	3.859
Big & LowBM	3.383	6.649	16.019	1.678	2.312	3.909
Big & HighBM	3.501	6.494	12.993	1.652	2.193	3.935

Table 3 shows average returns of two types of test assets. First, to allow comparisons with previous studies, Panel A shows average returns of portfolios sorted on size and BM using 16 portfolios (a 4x4 sort). As becomes evident, there is no clear pattern related to the size effect in these descriptive statistics as there are no significant *Small-Big* differences. In contrast, the differences regarding the book-to-market ratio are much more pronounced. The return differences *High-Low* are highly significant with T-values higher than 2.900 in all cases.

Table 3
Returns of SIZE, BM and DD portfolios

The table gives an overview of average returns within different portfolio structures. Panel A shows monthly returns in percent of the 16 value-weighted Fama and French portfolios. Portfolio differences, that is *High minus Low* and *Small minus Big* and its t-values are also displayed. t-values are calculated from a Dummy OLS-Regression with Newey-West standard errors. The dummy is created for two portfolio classes (e.g. big=1 and small=0). The truncation factor used within the regression is computed through a rule of thumb $l = \text{ceil}(3/4 \cdot T^{1/3})$. Panel B reports the monthly returns of the 2 x 2 x 3 test asset system with two SIZE, two BM and three DD classifications. Panel C uses the test assets system of Panel B to show the standard deviation of the returns and the mean number of companies within each portfolio. *,** and *** denotes significance at the 10%-, 5%- and 1%-level, respectively.

Panel A: Returns of the 16 Size/BM portfolios

	LowBM	2	3	HighBM	High-Low	t-stat
Small	0.017	0.522	0.347	1.243	1.226	(3.091***)
2	-0.460	-0.224	0.288	0.873	1.333	(3.337***)
3	-0.522	0.057	0.653	0.861	1.383	(3.111***)
Big	0.302	0.926	0.852	1.306	1.004	(2.905***)
Small-Big	0.285	0.404	0.505	0.063		
t-stat	(0.582)	(0.947)	(1.238)	(0.169)		

Panel B: Returns of the 12 portfolios

	LowDD	MedDD	HighDD	High-Low	t-stat
Small & LowBM	-0.346	0.531	0.646	0.992	(2.358**)
Small & HighBM	-0.278	1.124	0.093	0.371	(0.647)
Big & LowBM	-0.307	-0.550	1.454	1.761	(3.381***)
Big & HighBM	0.550	0.595	1.091	0.541	(1.478)

Panel C: Standard deviation of returns and number of companies within the 12 portfolios

	STD(returns)			mean number of companies		
	LowDD	MedDD	HighDD	LowDD	MedDD	HighDD
Small & LowBM	6.573	6.341	7.745	33.563	19.813	9.500
Small & HighBM	5.920	5.452	5.644	54.875	24.250	8.000
Big & LowBM	8.885	7.434	6.026	5.188	26.375	55.875
Big & HighBM	9.027	6.784	5.406	6.250	29.688	26.688

Panel B of Table 3 shows the average returns of portfolios sorted on the distance-to-default, firm size and book-to-market, where we use a 2x2x3 sort, resulting in 12 portfolios (our subsequent test assets for the asset pricing tests). There is a tendency of decreasing returns over all default risk-classes from high DD to low DD. The difference t-test indicates this relationship in 50% of the cases to be statically significant.

Finally, Panel C of Table 3 shows the standard deviation of the 12 portfolios returns and the average number of companies within each portfolio. The right hand part of Panel C shows that there is some tendency for companies with low DD to concentrate within small firms' portfolios. For example, the number of companies of the Small/Low DD groups is on average about 6 times higher than the numbers of companies within the Big/Low DD.

3.2 Factor Characteristics

To summarize the descriptive statistics in the preceding section, there is no indication from the univariate tests, that firm size affects average stock returns in Germany, and firms' default risk appears only weakly correlated with either BM or SIZE. This interpretation is supported by the correlation coefficients between the factors RMRF, SMB, HML, Δ(SV) and DEF, as reported in Table 4. Here, RMRF denotes the return of the CDAX in excess of the risk-free rate. The other factors are constructed as explained in Section 2.2.

Table 4
Descriptive Statistics of the Factors

The table reports means and standard deviations in percent per month for the period June 1990 to Mai 2006. Included factors are the market factor RMRF, the size factor SMB, the BM factor, the HML factor, the default factor Δ(SV) and the default factor DEF. RF denotes the risk free rate. The table also provides correlation coefficients between these factors.

Variable					Correlations					
	mean	std	min	max	RMRF	SMB	HML	DEF	Δ(SV)	RF
RMRF	0.283	5.792	-24.123	19.800	1.000	-0.391	-0.262	-0.010	0.475	-0.141
SMB	-0.497	3.648	-11.018	11.125		1.000	-0.101	-0.336	0.201	-0.011
HML	0.866	3.479	-14.052	16.969			1.000	-0.110	-0.018	-0.040
DEF	0.702	4.038	-13.679	12.026				1.000	-0.200	0.103
Δ(SV)	-0.032	0.506	-2.485	1.569					1.000	-0.078
RF	0.379	0.200	0.169	0.821						1.000

Table 4 shows that the correlation between RMRF and SMB (the size factor) and HML (the book-to-market factor) is negative and significant in terms of magnitude. The default-risk factor DEF is almost uncorrelated with the market factor, whereas the Δ(SV) factor has a correlation with the market of about 0.475. This already points to the fact that these measures are actually quite different. The correlation between the measure of Vassalou and Xing (2004), Δ(SV), and our excess-return factor DEF is only -0.200. Recall that Δ(SV) simply measures the change in aggregate (average) default risk, while DEF is the excess return of firms with a relatively low probability of default over firms with a relatively high PD.

Table 4 also provides summary statistics on the factor returns. The average market risk premium over the observation period is only 0.283% per month.

Similar to the results of Schrimpf, Schroeder, and Stehle (2006) for the German capital market, the average premium on the size-factor SMB is negative with -0.497% per month. The average premium on the default risk factor DEF is 0.702% per month. The mean value for Vassalou/Xing's factor Δ(SV) is close to zero, indicating that the average change in aggregate default risk is fairly small.

4 Results

4.1 Time-Series and Cross-Sectional Test

To test whether default risk is priced in the German capital market, we first consider the simultaneous time-series and cross-sectional GMM model with the moment conditions of equation (13). Table 5 shows the estimated factor sensitivities for the 12 (2x2x3) test assets sorted on SIZE, BM, and DD. The cross-sectional estimates of the risk premia are presented in Table 6.

Table 5 shows that all portfolios with a low distance-to-default (i.e. high default risk) load negatively on the default risk factor DEF, while portfolios containing firms with low default risk load positively. Interestingly, there is no comparable pattern visible for the Δ(SV) default risk factor proposed by Vassalou and Xing (2004). This demonstrates again that the two factors are very different measures, although they are intended as proxys for the same economic effect. Note that Vassalou and Xing (2004) generate their test assets also by sorting (implicitly) on the distance-to-default, so that our results should be directly comparable to theirs. Furthermore, all portfolios with high BM load positively on the HML factor whereas groups with low BM load negatively. This effect is observable in both models. As it turns out, again, the size factor does not show any pattern.

Panel C of Table 5 reports the results from a Wald test for the joint significance of the intercept terms of the two regression systems. Due to the high p-values, the null hypothesis of no unexplained returns on average needs to be rejected within the CAPM, the Fama/French and the Δ(SV) model, only the DEF model does not reject the null. Hence, according to this asset pricing test, a factor model including the factor DEF "fully" explain returns on the German stock market, whereas the Δ(SV) model does not.

Considering the estimates of the factor risk premiums in Table 6, the market risk factor premium RMRF is not significantly different from zero. This result is consistent with other studies on the German capital market (see for example Elsas, El-Shaer, and Theissen (2003)). As shown in Table 4, the realized market risk premium over the observation period is 0.283% per month with a standard deviation of 5.8%. Hence, relying on the moments of the empirical distribution over our observation period, the probability of a normally distributed random

Table 5

Time-series Estimates of Factor Sensitivities and the Test on the Intercepts

The table shows the estimated factor sensitivities from a time-series regression of the test asset portfolio returns on a varying set of factors. Panel A and Panel B compares the two models which contain the Fama and French factors and one default factor. Δ(SV) is the change in aggregate default risk, as suggested by Vassalou and Xing (2004), while DEF is the excess return of a portfolio of firms with low default risk over a portfolio of firms with high default risk. The values are computed using the two-stage GMM approach described in Section 2.3, simultaneously estimating time-series and cross-sectional regressions. The estimated factor risk premia from the cross-sectional regressions are shown in Table 6. The sample period is July 1990-June 2006. For the two different models we use the same test assets which have a 2 x 2 x 3 structure, that is, they are independently sorted on firm size, book-to-market and the distance-to-default. Panel C compares the CAPM, the Fama and French three factor model and the two models containing the default factors. The results of a Wald test are displayed in the row "Wald" with H_0: $\beta_{0,1} = ... = \beta_{0,N} = 0$ where $\beta_{0,i}$ is the intercept of portfolio i's regression. $E_i(\beta_0)$ describes the mean of the $\beta_{0,1} \ldots \beta_{0,N}$. *,** and *** denotes significance at the 10%-, 5%- and 1%-level, respectively.

Panel A: Factor Sensitivities and T-stats of the DEF model

Portfolio			β_{RMRF}		β_{SMB}		β_{HML}		β_{DEF}	
DD	SIZE	BM	Coef.	t-value	Coef.	t-value	Coef.	t-value	Coef.	t-value
Low	Small	Low	0.92	(19.11***)	1.01	(12.56***)	0.05	(0.79)	-0.40	(-4.97***)
Low	Small	High	1.03	(21.39***)	0.94	(14.48***)	0.55	(9.99***)	-0.11	(-1.82*)
Low	Big	Low	0.72	(8.86***)	-0.11	(-0.91)	-0.47	(-3.36***)	-1.26	(-9.81***)
Low	Big	High	0.93	(10.71***)	0.01	(0.09)	0.42	(2.49**)	-1.14	(-8.39***)
Med	Small	Low	0.85	(14.05***)	0.95	(8.14***)	-0.15	(-1.39)	-0.24	(-2.19**)
Med	Small	High	0.90	(18.01***)	0.75	(11.90***)	0.41	(6.01***)	-0.14	(-2.71***)
Med	Big	Low	1.08	(14.48***)	0.07	(0.60)	-0.13	(-1.20)	-0.18	(-1.87*)
Med	Big	High	1.00	(12.22***)	0.00	(0.05)	0.41	(4.20***)	-0.28	(-2.60***)
High	Small	Low	1.13	(12.36***)	1.16	(7.29***)	-0.03	(-0.22)	0.51	(3.87***)
High	Small	High	0.76	(10.07***)	0.84	(7.75***)	0.42	(5.49***)	0.34	(3.53***)
High	Big	Low	0.93	(24.38***)	-0.06	(-1.30)	-0.15	(-2.28**)	0.08	(1.50)
High	Big	High	0.78	(13.88***)	-0.09	(-1.22)	0.31	(3.54***)	0.17	(2.28**)

Panel B: Factor Sensitivities and T-stats of the Δ(SV) model

Portfolio			β_{RMRF}		β_{SMB}		β_{HML}		$\beta_{\Delta(SV)}$	
DD	SIZE	BM	Coef.	t-value	Coef.	t-value	Coef.	t-value	Coef.	t-value
Low	Small	Low	0.90	(9.97***)	1.10	(11.03***)	0.11	(1.36)	1.47	(1.78*)
Low	Small	High	0.99	(15.62***)	0.93	(12.80***)	0.55	(9.62***)	0.89	(1.90*)
Low	Big	Low	1.08	(6.38***)	0.69	(3.14***)	-0.07	(-0.39)	-2.34	(-1.43)
Low	Big	High	1.09	(6.55***)	0.54	(2.29**)	0.69	(2.93***)	0.63	(0.33)
Med	Small	Low	0.93	(8.18***)	1.12	(5.17***)	-0.07	(-0.67)	-0.68	(-0.64)
Med	Small	High	0.91	(11.78***)	0.80	(12.34***)	0.44	(6.37***)	0.30	(0.48)
Med	Big	Low	1.01	(12.33***)	0.05	(0.39)	-0.14	(-1.32)	1.57	(1.74*)
Med	Big	High	0.97	(11.95***)	0.06	(0.57)	0.44	(4.20***)	1.22	(1.35)
High	Small	Low	0.98	(8.54***)	0.83	(6.08***)	-0.19	(-1.44)	0.98	(0.87)
High	Small	High	0.73	(7.65***)	0.71	(5.83***)	0.35	(3.76***)	-0.50	(-0.63)
High	Big	Low	0.89	(16.90***)	-0.14	(-2.41**)	-0.18	(-3.05***)	0.53	(1.39)
High	Big	High	0.76	(10.24***)	-0.17	(-1.91*)	0.27	(2.93***)	-0.08	(-0.14)

Panel C: Wald Tests on the Joint Significance of Intercepts

	CAPM		Fama French		DEF model		Δ(SV) model	
Wald	34.472	(0.001***)	27.159	(0.007***)	16.393	(0.174)	28.650	(0.004***)
$E_i(\beta_0)$	-0.219	-	-0.153	-	0.006	-	-0.139	-

Table 6
Cross-sectional Estimates of Factor Risk Premia

The table compares the CAPM, the Fama and French three factor model and two models which contain the Fama and French factors and one default factor. The values are computed by a two-stage GMM approach using time-series and cross-sectional information at the same time. In this table only the cross-sectional results are displayed, time-series results can be found in table 5. The sample period is July 1990-June 2006. For the four different models we use the same test assets, that have a 2 x 2 x 3 structure, sorted on firm size, book-to-market, and the firms' distance-to-default. T-values are calculated with GMM using the Newey-West estimator for the spectral density matrix. The number of maximum lags is $l = 3$. *,** and *** denotes significance at the 10%-, 5%- and 1%-level, respectively.

		CAPM	Fama French	DEF model	Δ(SV) model
	variable	coef(t-val)	coef(t-val)	coef(t-val)	coef(t-val)
CROSS-SECTION	λ_{RMRF}	0.015	0.275	0.404	0.239
		(0.032)	(0.624)	(0.926)	(0.532)
	λ_{SMB}	-	-0.875	-0.876	-0.853
			(-3.044***)	(-3.046***)	(-2.965***)
	λ_{HML}	-	1.091	1.246	1.028
			(2.792***)	(3.160***)	(2.664***)
	λ_{DEF}	-	-	0.689	-
				(2.275**)	
	$\lambda_{\Delta(\mathrm{SV})}$	-	-	-	0.074
					(0.648)

variable to be negative (i.e. $r_M < r_f$) is about 48%. Under such conditions, the power of typical asset pricing test approaches is fairly low, see Elsas, El-Shaer, and Theissen (2003) and Pettengill, Sundaram, and Mathur (1995).

Table 6 further shows that the estimates of the risk premia for SMB, HML and the default risk factor DEF are significantly different from zero. The significant premiums of SMB and HML are almost unchanged, if the default risk factor is added, indicating that the book-to-market effect is not primarily driven by proxying for default risk, contrary to the suggestion and findings of Ferguson and Shockley (2003).

4.2 Factors Determining the Pricing Kernel

In what follows, we use the GMM discount factor model of section 2.3 with the moment conditions of equation (17) in the appendix to obtain estimates of and inference on factors determining the pricing kernel. This serves as a robustness test for the results from the times-series/cross-section analysis in the preceding section. Also, we report estimation results for the overall period sample 1990-2006 and the subperiods 1990-1998 and 1999-2006, to test the robustness of our results.

Table 7
Stochastic Discount Factor Test

This table reports the stochastic discount factor coefficient estimates computed by a two-stage GMM model over three time horizons (1990-1998, 1999-2006 and 1990-2006). The factor columns (RMRF, SMB, HML, Δ(SV) and DEF) contain in its rows marked with the year numbers the SDF coefficient estimates and in brackets the t-statistics. The remaining rows marked with "prem" show the estimated factor risk premia. Again t-statistics are reported in brackets. Furthermore, the column labeled J-test shows for each time horizon the results of a J test for overidentifying restrictions. We report the test statistic and the corresponding p-value (in parentheses). The premiums are measured in percent whereas the SDF coefficient estimates are presented x 10,000. T-values are calculated with GMM using the Newey-West estimator for the spectral density matrix. The number of maximum lags is $l = 3$. *,** and *** denotes significance at the 10%-, 5%- and 1%-level, respectively.

Panel A: 1990 - 2006

	RMRF	SMB	HML	DEF	Δ(SV)	J-Test
coef	1.76(1.40)	-	-	-	-	22.53(0.02**)
prem	0.02(0.03)	-	-	-	-	-
coef	2.83(1.67*)	-2.10(-0.78)	10.67(4.01***)	–	–	11.27(0.26)
prem	0.28(0.62)	-0.88(-3.04***)	1.09(2.79***)	–	–	–
coef	2.62(1.64)	-1.35(-0.53)	10.55(4.08***)	4.50(2.62***)	–	7.10(0.53)
prem	0.40(0.93)	-0.88(-3.05***)	1.25(3.16***)	0.69(2.27**)	–	–
coef	4.89(1.13)	0.19(0.04)	11.48(3.67***)	–	-32.03(-0.56)	10.34(0.24)
prem	0.24(0.53)	-0.85(-2.96***)	1.03(2.66***)	–	0.07(0.65)	–

Panel B: 1990 - 1998

	RMRF	SMB	HML	DEF	Δ(SV)	J-Test
coef	1.84(1.10)	-	-	-	-	21.60(0.03**)
prem	-0.20(-0.37)	-	-	-	-	-
coef	-1.40(-0.49)	-10.22(-2.78***)	5.99(2.03**)	–	–	14.24(0.11)
prem	0.17(0.35)	-1.05(-3.17***)	0.84(2.04**)	–	–	–
coef	0.90(0.31)	-6.03(-1.60)	8.65(3.11***)	6.83(3.71***)	–	8.94(0.35)
prem	0.34(0.71)	-0.96(-2.90***)	0.89(2.15**)	1.00(2.81***)	–	–
coef	10.09(1.67*)	3.25(0.46)	12.94(2.88***)	–	-278.46(-1.86*)	13.88(0.08*)
prem	0.11(0.20)	-1.06(-3.18***)	0.84(2.02**)	–	0.03(0.22)	–

Panel C: 1999 - 2006

	RMRF	SMB	HML	DEF	Δ(SV)	J-Test
coef	2.21(1.29)	-	-	-	-	13.58(0.26)
prem	0.40(0.41)	-	-	-	-	-
coef	2.99(1.77*)	4.11(1.27)	12.13(2.91***)	–	–	12.83(0.17)
prem	0.37(0.39)	-0.03(-0.05)	0.21(0.22)	–	–	–
coef	2.89(1.75*)	4.12(1.28)	12.45(3.02***)	0.09(0.03)	–	12.79(0.12)
prem	0.36(0.39)	-0.02(-0.04)	0.19(0.20)	-0.07(-0.13)	–	–
coef	10.13(2.50**)	12.68(2.15**)	19.01(4.53***)	–	-82.57(-1.71*)	11.20(0.19)
prem	0.40(0.43)	-0.07(-0.13)	0.36(0.43)	–	-0.02(-0.14)	–

Focusing first on the overall period 1990-2006, the results in Panel A of Table 7 show that only HML and DEF are factors systematically priced in the German capital market. Only for these factors, both the coefficient estimate for the pricing kernel weight (coef) and the risk premium estimate from the combined time-series / cross-sectional-regression risk premium (prem) are statistically different from zero. In contrast, the market risk factor and the default risk factor Δ(SV) suggested by Vassalou and Xing (2004) are insignificant according to both tests. SIZE has a significant risk premium, but does not significantly contribute to the pricing kernel.

These results remain broadly unchanged when running the asset pricing tests for different subperiods of time. Both Panel B and C illustrate that HML and DEF are the only factors that seem to explain equity returns in Germany systematically, no matter what type of asset rpcing test applied and what time period is used.

Finally, note that the estimated risk premium of DEF for the overall period (0.690% per month in overall period) and the factor contribution to the pricing kernel (4.50) indicate that equity returns are decreasing for firms more likely to default. This result corresponds to Dichev (1998) and other studies in the U.S., but contradicts the results by Vassalou and Xing (2004).

4.3 The Impact of Factor Construction

The preceding section has shown evidence that default risk is priced in the German capital market, supporting Vassalou and Xing (2004)'s general result. However, their default risk factor is not priced in the German capital market, and we actually find that equity returns decrease with higher default risk of firms. As a first step to understand these differences in results for the two countries, we replicate the study by Vassalou and Xing (2004) for the U.S. market and test whether the design of the factor matters for the U.S. market as well. Hence, we use the distances-to-default provided by Vassalou and Xing (2004), match these data with firms' accounting information from Compustat, and market capitalization from CRSP. Using these data, we construct our DEF factor for the U.S. market. [12]

The test portfolios for the U.S. market are constructed using the 3 x 3 x 3 sort of book-to-market, size and default risk . The results of the asset pricing tests are shown in Table 8.

Panel B shows the results of the Δ(SV) model used by Vassalou and Xing (2004). As becomes evident, we're only partly able to reconfirm their results. The coefficient on Δ(SV) in the stochastic discount factor test is statistically not significant from zero, while the estimated risk premium taken from the joint GMM time-series / cross section-regression differs significantly from zero. The difference in the results comes technically from the fact that we have not been able to fully reconstruct Vassalou/Xing's sample. Using the matched Compustat and CRSP database leads to roughly 10% less sample firms than in their data. Economically, however, this demonstrates that the

[12] Since the DD information comes from Vassalou and Xing (2004), the sample period is is now January 1971 to December 1999. The Fama/French factors and the risk-free rates are downloaded from the Kenneth R. French Homepage.

Table 8
DEF and Δ(SV) on the American market

This table provides the stochastic discount factor coefficient estimates and the cross-sectional test estimates over the time horizon 1971-1999 for the US market. The data is from CRSP. Panel A shows the results of the Fama/French model augmented by "DEF"and Panel B the results of the Fama/French model augmented by "Δ(SV)". The factor columns (RMRF, SMB, HML, Δ(SV) and DEF) contain in its rows marked with the coefficient label the SDF coefficient estimates and in brackets the t-statistics. The remaining rows marked with "prem" show the estimated factor risk premia. Again t-statistics are reported in brackets. Furthermore, the column labeled J-test shows the results of a J test for overidentifying restrictions. We report the test statistic and the corresponding p-value (in parentheses). The premiums are measured in percent whereas the SDF coefficient estimates are presented x 10,000. T-values are calculated with GMM using the Newey-West estimator for the spectral density matrix. The number of maximum lags is $l = 3$. *,** and *** denotes significance at the 10%-, 5%- and 1%-level, respectively.

Panel A: DEF

	RMRF	SMB	HML	DEF	Δ(SV)		J-Test
coefficient	1.658	2.016	-2.074	1.153	-	Statistic	40.598
t-value	(0.871)	(0.666)	(-0.538)	(0.367)	-	p-value	(0.013**)
premium	0.367	0.387	-0.677	-0.135	-	-	-
t-value	(1.414)	(2.030**)	(-3.106***)	(-0.860)	-	-	-

Panel B: Δ(SV)

	RMRF	SMB	HML	DEF	Δ(SV)		J-Test
coefficient	-0.490	-2.302	-5.080	-	10.192	Statistic	34.938
t-value	(-0.170)	(-0.579)	(-1.218)	-	(0.547)	p-value	(0.053*)
premium	0.388	0.318	-0.831	-	0.405	-	-
t-value	(1.499)	(1.715*)	(-3.813***)	-	(3.532***)	-	-

Vassalou and Xing (2004) are not fully robust to slight changes in the firm sample. This observation becomes event more pronounced by the results shown in Panel A of Table 8. It provides the results of the model that includes the Fama/French factors and our factor DEF, which is constructed of using the idea of self-financing portfolios to generate asset pricing factors, as pioneered by Fama/French. This alternative default factor does not show any significance in explaining stock returns in the U.S. market.

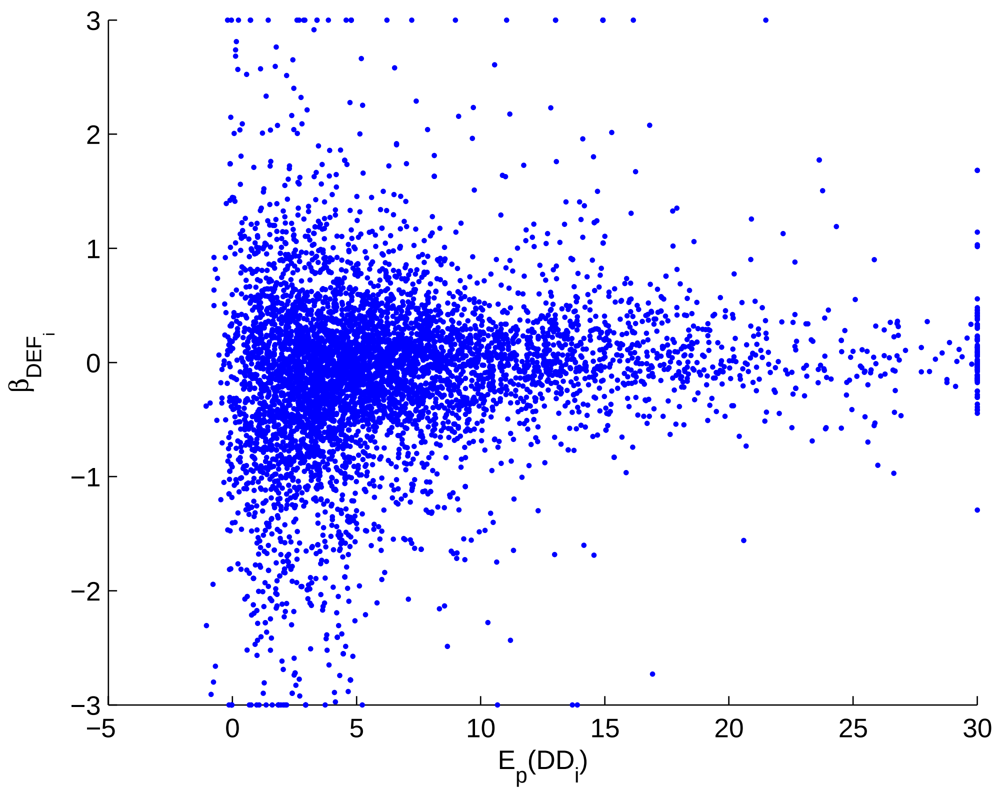
Overall, the explanatory power of a default risk factor in the U.S. (and Germany) depends much on how it is constructed, which clearly implies the need for further research. Still, the DEF factor has a strong and significant impact on stock returns in Germany in our observation period.

5 What drives Default Risk Sensitivities?

Figure 1 shows a scatterplot of firm's market default factor sensitivities and the individual distances-to-default. We calculate the default factor sensitivities β_{DEF_i} by rolling 5-year time-series regressions of firms' returns on the DEF

Fig. 1. Scatter Plot of Firms' Default Factor Sensitivities and their Individual Distances-to-Default

The scatter plot illustrates the dependency between firms' default factor sensitivities (y axis) and the individual distances-to-default (x axis). The default factor sensitivities are calculated by rolling 5-year time-series regressions (60 observations) of firms' returns on the four factors RMRF, SMB, HML and DEF. Using rolling windows shifted by one year, a maximum number of 13 observations for each firm is possible (1990-1994, 1991-1995... 2002-2006). The DD values are calculated as the mean of the individual distances-to-default over each of these rolling time windows. DD values greater than 30 and factor sensitivities greater than 3 and smaller than -3 are winsorized.



model (including the other Fama/French factors).[13] This leads to at most 13 observations for each firm, one for each five year period (1990-1994, 1991-1995... 2002-2006). The DD values $E_p(DD_i)$ are calculated as the mean of the individual DD over one period at a time. We use the subscript p to address a certain 5-year period. DD values greater than 30 and sensitivities greater than 3 and smaller than -3 are winsorized to reduce the impact of extreme observations. Firms with distances-to-default greater than 30 do not perform very different from firms with a DD o0f 30 since their default probability is extremely close to zero anyway.

[13] Only companies with at least 12 monthly observations within the 5-year window are included.

The figure demonstrates that there is no clear or even linear relationship between a firm's individual default risk and it's default factor sensitivity. To take a closer look at tghe determinants of default factor sensitivities, we run regressions based on the following model

$$\beta_{DEF_{ip}} = \delta_0 + \delta_1 E_p(DD_i) + \delta_2 \left[E_p(DD_i)\right]^2 + \delta_3 d_1 + ... + \delta_{P+2} d_P + \nu_i + \epsilon_{ip}$$

where $\beta_{DEF_{ip}}$ is the default factor sensitivity of firm i in period p. The dummy variables d_p denote the period and ν_i describes the firm specific (fixed) effect. Within the model, a squared term is also included as we expect that $E_p(DD_i)$ is not enough to explain the default sensitivity. First, a pooled OLS regression without dummies and firm-specific fixed effects has been set up (OLS). Second, a fixed effects model including period dummies is estimated (FE). And finally, to check against symmetry problems, we run a third regression that differs from the second model only in in that the sensitivity measured using their absolute value (FE_{abs}), thus testing what drives the intensity of factor sensitivity and not its sign.

Table 9
Factor Sensitivity Regressions?

This table reports the results of three regressions of firms' default factor sensitivities on the individual DD and squared DD. The default factor sensitivities are calculated by rolling 5-year time-series regression (60 observations) of firms' returns on the four factors RMRF, SMB, HML and DEF. Using rolling windows shifted by one year, a maximum number of 13 observations for each firm is possible (1990-1994, 1991-1995... 2002-2006). The DD are calculated as the mean of the individual DD over the same time period. DD greater than 30 and sensitivities greater than 3 and smaller than -3 are winsorized. The first two rows of the table describe the results of a pooled OLS regression. The second two rows present the results of a fixed effects regression including time period dummies as well. The third two rows illustrate a fixed effects regression of the absolute value of firm default factor sensitivities on the individual DD, squared DD and time period dummies. The intercepts of the FE models are means of the fixed effects weighted by the individual number of periods. t-statistics are in parenthesis. *,** and *** denotes significance at the 10%-, 5%- and 1%-level, respectively.

OLS vs. Fixed Effects

		intercept	$\delta_{1,E(DD)}$	$\delta_{2,E(DD)^2}$	R^2
OLS	coef	-0.22568	0.02230	-0.00014	0.02086
	t-value	(-7.09593***)	(6.52171***)	(-5.07381***)	-
FE	coef	-0.16512	0.02082	-0.00007	0.01738
	t-value	-	(6.71248***)	(-1.94467*)	-
FE_{abs}	coef	0.61779	-0.00658	0.00003	0.01907
	t-value	-	(-2.80794***)	(0.92947)	-

The results of the three regressions are summarized in Table 9. The first two regression lead to similar results in terms of the coefficient. The intercepts are negative, the distance-to-default is positively correlated with the default sensitivity and the squared term correlates negatively with the default sensitivity. All values are highly significant though the very small R^2 values show a very low dependency between the dependent and the independent variables. The FE_{abs} regression reports a slightly higher R^2 than the FE regression but finds a negative relationship between DD and β_{DEF}. Note that the firm fixed effects control for all firm characteristics that do not change over time (like for example industry affiliation), while the time dummies control for all time-variant factors that do not change across firms, like for example the interest rate level, and other macro-variables. F-tests on the joint significance of the firm fixed effects are highly significant, as are similar test for the time dummies. Hence, firm groups like industries and macro-factors explain a significant amount of the observed variation in firms' default factor sensitivities. Most importantly, however, these results clearly demonstrate that a higher firm specific default risk does not necessarily lead to a higher sensitivity to the systematic (non-diversifiable) default risk factor priced in the market.

6 Conclusions

This study examines the impact of default risk on equity returns in Germany, using the Merton (1974) model, and thus relying on forward-looking and timely market data to estimate firms' default risk. We contribute to the literature along several dimensions. Most importantly, since it is rather unclear whether default risk has a systematic (non-diversifiable) component and if so, why, the analysis of German data allows to test the validity of the seminal study by Vassalou and Xing (2004) for the U.S. market. The German financial system is the prime example for a bank-based financial system, and it is to be expected that if the impact of default risk on returns depends on the characteristics and relevance of debt financing for corporate finance, this effect should be more pronounced for German rather than U.S. companies.

Second, we extend the work by Vassalou and Xing (2004) by using a alternative default risk factor which is measured as an excess return of a portfolio of firms with low default risk over a portfolio of firms with high default risk, much in the spirit of the Fama and French (1993) HML and SMB factors. This bases the asset pricing test directly on a market price of risk, rather than a measure of the change in aggregate default risk, as in Vassalou and Xing (2004). Our empirical results show the importance of this difference. The default risk factor measured similar to Vassalou and Xing (2004) lacks any significance and does not contribute to the pricing kernel in the German capital market. The default risk factor measured as a return is systematically priced in Germany, however.

The risk premium for bearing market default risk is negative, since our estimate for the risk premium of the default risk factor is positive, i.e. firms with low PD have on average lower returns than firms with high PD. This contradicts again the findings by Vassalou and Xing (2004), but is in line with other studies on the U.S. market (e.g. Dichev (1998) and Ferguson and Shockley (2003). To elaborate on these differences between the German and the U.S. market results, we conduct two tests. The first replicates the Vassalou and Xing (2004) study, using their data (and about 90% of their sample firms) and tests whether a default risk factor constructed as a self-financing portfolio is systematically priced in the U.S. This turns out not be the case, and actually the default risk factor suggested by Vassalou and Xing (2004) performs in the this slightly smaller sample much worse than in the original study. These finding raise some doubts on the robustness of the results for Germany and the U.S. and requires future research. In a second tests, we explore what drives the default factor sensitivities of firms in Germany to get an understanding of the economic determinants of default risk as a systematically priced risk factor in equity returns. It turns out that there is no linear relationship between firms individual default risk and the their default factor sensitivity, that is, firms with a high PD are not necessarily also firms with a sensitvity against the non-diversifiable (market) default risk component. We find evidence that default factor sensitivities are driven by macro-variables and firm fixed effects like the industry affiliation. Though a fist step, these results again demand future research to improve our understanding of what drives systematic default risk.

In summary, we find evidence consistent with default risk being a systematic factor priced in capital markets. Further, our analysis shows, that this risk is only barely related to the firm size and market-to-book factors advocated by Fama/French. Our estimates indicate that higher market default risk sensitivity leads to lower returns.

Appendix

In this section, the econometric methods used within this paper are described in detail. First, we use a GMM approach to estimate simultaneously the time series and cross sectional test. The following (K+2)$\cdot$N x 1 system can be used to compute the estimates of the coefficient vector $\boldsymbol{\Theta}$:[14]

$$g_T(\boldsymbol{\Theta}) = \begin{bmatrix} E_t[(\boldsymbol{R}_t^e - [\boldsymbol{\alpha} \;\; \boldsymbol{\beta}]\boldsymbol{X}_t) \otimes \boldsymbol{X}_t] \\ E_t(\boldsymbol{R}_t^e - \boldsymbol{\beta}\boldsymbol{\lambda}) \end{bmatrix} = \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \end{bmatrix} \tag{13}$$

where K denotes the number of factors used in the model[15] and N is the number of test assets. E_t describes the mean over t. The expression $[\boldsymbol{\alpha} \;\; \boldsymbol{\beta}] = [\boldsymbol{\alpha} \;\; \boldsymbol{\beta_1} \;\; \boldsymbol{\ldots} \;\; \boldsymbol{\beta_K}]$ denotes a matrix consisting of $\boldsymbol{\alpha}$, a N x 1 vector of intercepts and $\boldsymbol{\beta} = [\boldsymbol{\beta_1} \;\; \ldots \;\; \boldsymbol{\beta_K}]$ which is a N x K matrix of time-series sensitivities. The variable $\boldsymbol{\lambda}$ describes a K x 1 vector of cross sectional coefficients. It is important to note that there is no intercept term within our cross sectional approach. $\boldsymbol{R}_t^e$ identifies the N x 1 excess return vector with returns of all test asset portfolios $p = \{1 \ldots N\}$ at time $t \in \{1 \ldots T\}$. $\boldsymbol{X}_t' = [1 \; X_{2,t} \;\; \ldots X_{K+1,t}]$ is a horizontal vector composed of 1 and the factor values depending on t. The symbol $\otimes$ denotes the Kronecker product and $\boldsymbol{\Theta}$ describes the ((K+1)N+K) x 1 parameter vector containing all mentioned parameters.

$$\boldsymbol{\Theta}' = [\boldsymbol{\alpha}' \;\; \boldsymbol{\beta_1}' \;\; \ldots \;\; \boldsymbol{\beta_K}' \;\; \boldsymbol{\lambda}'] \tag{14}$$

The system of moment conditions leads to an overidentification (w.r.t. the market risk premia of the factors) since (K+2)N $\geq$ (K+1)N+K.
The GMM estimate can be computed by

$$\hat{\boldsymbol{\Theta}} = \arg\min_{\boldsymbol{\Theta}} g_T(\boldsymbol{\Theta})' \hat{\boldsymbol{S}}_{\mathbf{1}}^{-1} g_T(\boldsymbol{\Theta}) \tag{15}$$

where $\hat{\boldsymbol{S}}_{\mathbf{1}}^{-1}$ denotes the estimated inverse spectral density matrix using the Newey and West (1987) approach.

Since in the cross sectional test, portfolio returns are regressed on estimated betas, this test would suffer from an errors-in-variables problem. Estimating the time series and cross-section parameters simultaneously explicitly accounts for this effect of generated regressors, because the standard errors are adjusted accordingly through the use of the optimal weighting matrix in GMM.

The moment conditions map the time-series regressions

$$\boldsymbol{R}^{ei} = [\alpha^i \;\; (\boldsymbol{\beta}^i)']\boldsymbol{X} + \boldsymbol{\epsilon}^i \quad , \quad i = 1 \ldots N$$

[14] Vectors or matrices are indicated by bold letters.
[15] Using only the three Fama and French factors, K would be 3.

and cross-sectional regressions

$$\boldsymbol{R}_t^e = \boldsymbol{\beta}\boldsymbol{\lambda} + e_t \quad , \quad t = 1 \ldots T$$

into a GMM system. $\boldsymbol{R}^{ei}$ denotes the T x 1 excess return vector of test asset i whereas α^i is the intercept of the portfolio i's time-series regression. $\boldsymbol{\beta}^i$ describes the K factor sensitivities, $\boldsymbol{X}$ is the usual T x (K+1) factor matrix and $\boldsymbol{\epsilon}^i$ is the regression's error term. $\boldsymbol{\lambda}$ denotes a K x 1 vector of cross-sectional variables. $\boldsymbol{\beta} = [\boldsymbol{\beta}^1, ..., \boldsymbol{\beta}^N]'$ describes the N x K matrix of betas obtained from the time series regression. $\boldsymbol{e}_t$ is a N x 1 error term at time t and the N x 1 vector $\boldsymbol{R}_t^e$ denotes again the excess returns of all N test assets at time t. Using this approach for the CAPM, the Fama and French model and the two models with additional default factors included, we are able to compare these specifications. It is important to note that the two new models are composed of the three Fama and French factors and just one of the two default factors Δ(SV) and DEF. Since only the four factor model including DEF employs factors measured as returns, this is our preferred specification.

Second, an asset pricing model can be written in its stochastic discount factor (SDF) form,

$$p_t = E_t[m_{t+1} \cdot x_{t+1}] \tag{16}$$

where p_t is the price at time t for the expected payoff x_{t+1} at $t+1$ multiplied by the stochastic discount factor m_{t+1}. Assigned to our models, the form can easily be changed into

$$E_t[m_{t+1}(R_{p,t+1} - r_{t+1})] = 0 \tag{17}$$

where

$$m_{t+1} = [\ a \quad -\boldsymbol{b}'\ ]\boldsymbol{X}_{t+1} \tag{18}$$

and $\boldsymbol{b}$ denotes the K x 1 parameter vector of the SDF whereas a describes the intercept. If p_t is zero, b is identified only up to a constant ($0 = E(mx) = E(2mx)$). In that case Cochrane (1996) proposes to impose a arbitrarily (e.g. $a = 1$). To compute and test this form, a GMM/discount factor model can be specified with the following moment conditions:

$$\boldsymbol{g_T}(\boldsymbol{b}) = E_t[(\boldsymbol{R}_t^e)(X_{2,t} \ \ldots X_{K+1,t})\boldsymbol{b} - \boldsymbol{R}_t^e] \tag{19}$$

where $\boldsymbol{g_T}(\boldsymbol{b})$ is a N x 1 vector. The optimization problem is very similar to equation (15), that is,

$$\hat{\boldsymbol{b}} = \arg\min_{\boldsymbol{b}} \boldsymbol{g_T}(\boldsymbol{b})'\hat{\boldsymbol{S}}_{\boldsymbol{2}}^{-1}\boldsymbol{g_T}(\boldsymbol{b}). \tag{20}$$

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