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The Relevance of Banks to the European Stock Market

Abstract

Banks have always played an ambivalent role in financial markets. On the one hand, they provide essential services for the market; on the other hand, problems in the banking sector can send shock waves through the entire economy. Given this prominent role, it is not surprising that Pereira and Rua (2018) found that the health of the banking sector exerts an influence on stock returns in the US. Understanding the relationship between banks and their impact on the asset prices of non-financials is essential to evaluate the risk emanating from an unhealthy banking sector and should be considered in new regulatory requirements. The aim of this study is to determine if the health of European banks is of such importance for the European stock market so that spillover effects are visible. Our results show that none of our banking-health variables have explanatory power on the cross-section of European stock returns. These findings contrast those for the US. The reasons may be manifold, from an unimportant liquidity provisioning channel over reduced room for actions due to regulatory requirements up to a moral hazard situation in Europe, where investors strongly rely on the governmental bailouts of distressed banks.

JEL-Codes: G120, G210.

Keywords: asset pricing, banking, spillover, errors-in-variables, individual stocks, distance-to-default.

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1. Introduction

Banks play an essential role in the proper functioning of financial markets as the main source of liquidity for many companies, as well as for the real economy. The shock waves to the market during the subprime mortgage crisis from 2007 onward and the bankruptcy of Lehman brothers led to a (nearly) global recession. This underlines the problems that a 'sick' banking sector can cause. Therefore, it seems reasonable that the health of the banking sector is crucial for the functioning of an economy and might thus be a priced factor in asset pricing models. The recent study of Pereira and Rua (2018) supports this hypothesis for the US market. The aim of this study is to identify a similar relationship between the banking sector's health status and the cross-section of stock returns to evaluate these spillover-effects in the European stock market. Therefore, we outline the importance of a healthy banking sector. However, we do not want to add another factor to the 'factor zoo'.[1]

The idea of using the informatory power in financial institutions' measures of risk is an approach widely used in academic research. Allen, Bali, and Tang (2012) use different bank-specific value-at-risk measures to calculate a systemic risk indicator, called CATFIN. They were thus able to forecast macroeconomic downturns 6 months in advance using different datasets for different regions. Adrian, Etula, and Muir (2014) use the broker-dealer-leverage as a single factor to explain the cross-section of stock returns. In their study, the one-factor model outperformed the three-factor-model of Fama and French (1992) (FF-3 model). The recent work of Mihai (2020) uses a more macroeconomic approach, namely the expansion (decline) in debt per capita as a proxy for credit expansion (contraction) as an additional risk factor in asset pricing models, with promising results.

Pereira and Rua (2018) show that their so-called BANK factor, based on the market value weighted average distance-to-default (DD) of banks, can be considered a priced factor in the cross-section of stock returns of American non-financial firms. The DD measure originates from the work of Crosbie and Bohn (2003). It is used by Moody's

1. For example, Cochrane (2011) calls the immense number of identified factors in asset pricing a 'zoo of factors' and Harvey, Liu, and Zhu (2015) identified 316 factors in various scientific articles. The recent study of Hou, Xue, and Zhang (2020) documented as many as 452 factors.

KMV to determine the Expected Default Frequency, which describes the probability of default for a company and serves as one factor for Moody's rating. Vassalou and Xing (2004) are the first to employ this metric in asset pricing models by using their default likelihood indicator (DLI) for the default probability of a company. They find that the DLI contains different information than credit default swap (CDS) spreads and adds explanatory power to the FF-3 model. Although Eugene Fama and Kenneth French argue that their size and value risk premiums already account for default risk, Vassalou and Xing (2004) deduce, based on their findings, that only part of the default risk is captured by these two factors. The work of Pereira and Rua (2018) is motivated by the idea that the DD of the banking sector contains information on future economic activity in the real economy. This would make it a state variable in the spirit of the ICAPM of Merton (1973).

Studies that focus on the European stock market are challenging for several reasons. First, from a historical viewpoint, Europe cannot be considered as a single integrated market, but as several connected independent markets. Second, data availability is limited compared to the long time series available for the US stock market. Finally, the banking culture is different among European countries.[2] Since the 1999 introduction of the euro as the common currency for the European Monetary Union (EMU), the Eurozone can be considered a common market. Therefore, we start our analysis in 1999. Having a short analysis period of approximately two decades has advantages and disadvantages. On the one hand, the results do not suffer from historical effects, as they might have already vanished due to structural transformation (e.g., the role of banks in supplying companies with liquidity might have been more important in the 1960s and the 1970s than from 2000 onward). On the other hand, there are fewer events for which a bank crisis leads to (possible) liquidity shortages and, therefore, impact the real economy.

We use a dataset consisting of the 19 EMU countries plus the United Kingdom (UK) and Switzerland—referred to as EMU+. The latter two were added because

2. For example, the German banking market is divided into private banks that are usually listed, the so-called Sparkassen, and cooperative banks. Private banks account for only around 25% of the overall total assets Deutsche Bundesbank (2021). Therefore, the main part of the banking activity in Germany is not visible to analyze at the stock market level.

they have very advanced banking systems, which might also be relevant when creating the BANK risk factor to be used in asset pricing models for Europe. Furthermore, the addition of the United Kingdom and Switzerland enables us to analyze more country compositions, thus adding further variability to the analysis. Unless otherwise indicated, we used the EMU+ dataset. The general results are stable for EMU-only countries (referred to as EMU), excluding Germany (EMU+ ex DE and EMU ex DE), and also for country-specific analyses such as the UK-only one.

We use three factors as proxies for the health of the banking sector in our sample. First, we reproduce BANK from Pereira and Rua (2018), since they show by using their US sample that this measure contains predictive power over the returns of non-financials. Second, we utilize the monthly relative change of a credit default swap index based on banking stocks, as e.g. Chiaramonte and Casu (2013) find that CDS spreads account well for bank riskiness. Finally, we implement a bank-spanning factor in a similar fashion to the insurance spanning factor of Ben Ammar, Eling, and Milidonis (2018).

The remainder of this paper proceeds as follows. In Section 2, we specify how the factors used in our analysis are created. In Section 3, we present the datasets and data items. Section 4 shows the setting up of our asset-pricing tests. Next, we present the results in Section 5. We conclude with Section 6.

2. Factor creation

We use three different variables to examine the influence of the banking sector's stability on the cross-section of non-financial stock returns. First, we use a European version of the BANK factor, proposed by Pereira and Rua (2018), as a proxy for distress in the financial community. Second, we use the monthly percentage change of the 'DS Europe Banks 5Y CDS Index €', as provided by Datastream (referred to as dCDSS). Finally, we use a long-short portfolio based on the market value-weighted returns of banking institutions minus the market portfolio, as inspired by Ben Ammar, Eling, and Milidonis (2018). We call this factor 'banks minus market' (BMMkt), using the collective overperformance (underperformance) of banking shares as a measure of this sectors health. Furthermore, using our sample, we calculate the time series factors (TSF) used in the five-factor model of Fama and French (2015). To check result robustness, we use two versions of these factors in our analysis: winsorized (at the 1% and 99% levels) and unwinsorized. The main results are stable regardless whether we winsorize the factors. Unless otherwise indicated, we used the unwinsorized version of the factors throughout this article.

2.1. Creation of BANK

Equation (1) shows that BANK is defined as the change in the market value-weighted distance-to-default (VWDD) across all banks, scaled with an arbitrary factor of 0.01 to adjust the magnitude of the regression coefficients in the subsequent analysis. The intuition is that, if there is a decrease (increase) in VWDD, BANK becomes negative (positive), indicating the decreasing (increasing) health condition of the banking sector and exerting a negative (positive) influence on the cross-section of the stock returns of non-financials. Following Pereira and Rua (2018), for the calculation of BANK, only the stocks with Standard Industrial Classification (SIC) codes between 6020 and 6038 that have a track record for at least one year are considered. During this one-year period, we require a coverage of return data of at least 66%. By calculating DD, equation (2) projects the current value of assets $V_{i,t}$ in the future in one year.[3] The value of debt that is due in one year, $F_{i,t+1}$, is then subtracted from this value and standardized by $\sigma_{i,t}$.

$$BANK_t = 0.01 \sum_{i=1}^{I} (DD_{i,t} w_{i,t} - DD_{i,t-1} w_{i,t-1}), \tag{1}$$

where

$w_{i,t}$ = weight of company i at time t

3. In the original formulas, a factor τ defines the extent to which $V_{i,t}$ is projected into the future. Because τ equals one year in the referenced publications, as well as in our analysis, we refrain from explicitly mentioning it in the subsequent formulas.

and

$$DD_{i,t} = \frac{lnV_{i,t} + (\mu_{i,t} - \frac{\sigma_{i,t}^2}{2}) - lnF_{i,t+1}}{\sigma_{i,t}}, \tag{2}$$

where

$V_{i,t}$ = current value of assets of company i,

$\mu_{i,t}$ = drift of $V_{i,t}$,

$\sigma_{i,t}$ = volatility of $V_{i,t}$,

and $F_{i,t+1}$ = value of debt of company i, which is due in one year.[4]

Because value of assets $V_{i,t}$ as well as its standard deviation $\sigma_{i,t}$ and drift-component $\mu_{i,t}$ are not directly observable in the market, they must be calculated in a previous step. To this end, we use the model of Merton (1974), which states that the observable value of equity $S_{i,t}$ can be interpreted as the price of a European call option on the value of assets, with a strike price equal to the 'promised payment [...] to the debtholders' (p. 453). Therefore, the required variables can be created using equation (3) of Black and Scholes (1973):

$$S_{i,t} = V_{i,t}N(d_1) - F_{i,t+1}e^{-i}N(d_2), \tag{3}$$

where

$$d_1 = \frac{ln(\frac{V_{i,t}}{F_{i,t+1}}) + (i + \frac{\sigma_{i,t}^2}{2})}{\sigma_{i,t}},\ d_2 = d_1 - \sigma_{i,t}$$

and i = one-year risk-free-rate.

4. Proxied by the Worldscope item 'Short Term Debt & Current Portion Of Long Term Debt' reported on fiscal year end for t-1 or t-2. Following Vassalou and Xing (2004), we use t-2 data for the first four months after the fiscal year end for the respective company. Afterwards, we use t-1. This is to avoid reporting delay issues and, therefore, risking a lookahead bias of our DDs.

Equation (3) must be solved for two unknown variables $V_{i,t}$ and its volatility $\sigma_{i,t}$. Vassalou and Xing (2004) propose an iterative procedure for this task. At the end of every month, they produce a daily time-series of V_is for the previous year using the volatility of observed daily returns as a proxy for the value of assets' standard deviation in the first iteration, $\sigma_{i,t}$. The newly created time-series of V_is is used to estimate a new $\sigma_{i,t}$, which is then used in the next iteration. The procedure is repeated, always using the newest $\sigma_{i,t}$, until the difference between the actual estimate of $\sigma_{i,t}$s and the previous one is $<= 10^{-4}$ for two consecutive iterations.[5] From this final timeseries of V_is, drift $\mu_{i,t}$ is calculated as its average growth rate. After the above parameters are calculated, we use them to obtain the monthly DD for each bank using equation (2). Before calculating VWDD and BANK using equation (1), we further follow Pereira and Rua (2018) and truncate the DDs at -3 and +5 to limit the influence of outliers.

Figure 1 shows the VWDD as created from the EMU+ dataset from January 1993 to June 2020. There is a dramatic decrease in the VWDD from 2007 until 2009, which marks the subprime mortgage crisis and the subsequent global banking crisis. This period was threatening to the entire banking sector in Europe, as reflected in the graph. Since VWDD is an average, many banks in the sample had a DD of 0 or even negative, indicating bankruptcy. This was avoided due to interventions from governments and central banks. To illustrate the severity of the situation during the banking crisis, we observe that between October and December 2008 around 18% (or 28) of all active banks in our sample were bankrupt in terms of their DD.

5. Usually, a result is found after a few iterations. We limit the maximum number of iterations to 300. If no result can be obtained, we set DD to NA for that month. This usually occurs only for stocks with very low initial volatility, which indicates illiquid stocks.

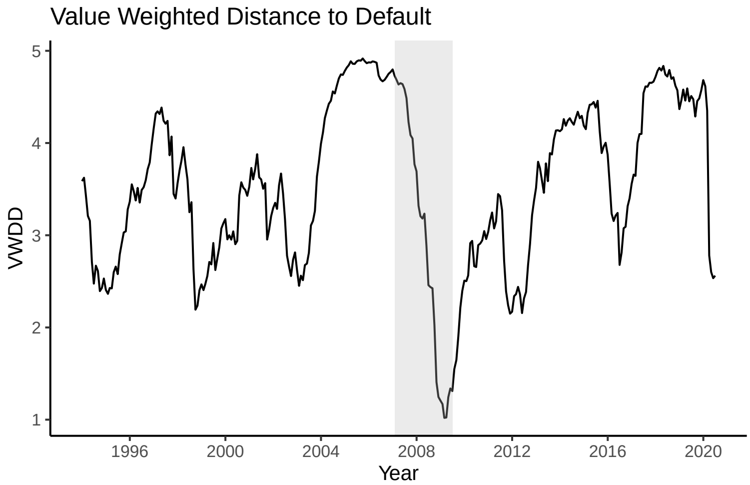

Figure 1. Value weighted distance-to-default of EMU+ from January 1993 to June 2020.

2.2. Creation of the Bank spread factor

To proxy the distress in the banking sector, we also consider a factor that can be considered as a traded portfolio long in banking stocks and short in the entire market portfolio. Therefore, we call our factor BMMkt, which stands for banks minus market. We also considered creating this factor using the market value weighted returns of all non-banks as subtrahend to create a full self-financing portfolio. Since both timeseries are nearly identical (they have a correlation of 99.72% and a t-value of 1.0225 for H_0: the difference is 0) we decided on the approach of Ben Ammar, Eling, and Milidonis (2018). BMMkt is calculated as per equation (4). As bank stocks, we define stocks with SIC codes between 6020 and 6036 (including boundaries). This is the same definition used by Pereira and Rua (2018) and considers only institutions whose main business activity is lending.

$$BMMkt_t = R_{banks,t} - MKT_t, \tag{4}$$

where $R_{banks,t}$ is the value-weighted returns of banking stocks and MKT_t is the market portfolio.

The intuition of this factor is easy to understand. In the case of distress in the banking sector, there should be relative underperformance compared to the market, creating the expected spillover effects. We expect this factor to perform in a similar manner as BANK, since the market value is (besides volatility) a significant factor in calculating BANK. Therefore, BMMkt might be a straightforward substitute to the rather complex numerical procedure required to obtain BANK.

2.3. Creation of other time series factors

To create our TSF, we follow the commonly used approach of creating so-called factor-mimicking portfolios. Their construction is based on stock's characteristics. We exclude financial firms (SIC codes between 6000 and 6999) when creating our TSF, following Fama and French (1992) and Hanauer and Huber (2018).

Replicating the five-factor model of Fama and French (2015) (FF-5 model) using our sample is the basis of the analysis. The size factor is the market value of stocks at the end of June. The value factor is the book-to-market-ratio (BM)[6] at the end of the previous year and the investment factor is defined as $Inv = \Delta Total\ assets_{t-1}/Total\ assets_{t-2}$. Furthermore, we use the cash based gross profitability (CbGP) of Hanauer and Huber (2018), which is defined as follows:

6. We use the sum of 'common shareholders equity' and 'deferred taxes' from Datastream as book value. All data items used, are listed in Table A2 in the Appendix.

$$
\begin{aligned}
CbGP =& \frac{GP_{t-1} + cba_{t-1}}{Total\ assets_{t-1}} \\
&with \\
GP_{t-1} =& Sales_{t-1} - Cost\ of\ goods\ sold_{t-1} \\
&and \\
cba_{t-1} =& -\Delta Accounts\ receivable_{t-1} - \Delta Inventory_{t-1} \\
& - \Delta Prepaid\ expenses_{t-1} + \Delta Deferred\ revenue_{t-1} \\
& + \Delta Trade\ accounts\ payable_{t-1} + \Delta Accrued\ payroll_{t-1} \\
& + \Delta Other\ accrued\ expenses_{t-1}.
\end{aligned} \tag{5}
$$

In June of each year, we calculate the so-called factor-mimicking portfolios for size (SMB), value (HML), profitability (RMW), and investment (CMA), using the 2 x 3 sorts of Fama and French (2015). Following their approach, we independently sort our stocks into two size portfolios and three portfolios based on the characteristics BM, profitability, and investment (referred to as CBP). As breakpoints, following Fama and French (2017), we use the 10% quantile of the aggregate market value for size and the 30% and 70% quantiles of big stock's characteristics. By intersecting the size portfolios with the CBP, we obtain six portfolios per characteristic, for which we calculate the market value-weighted portfolio return. HML, RMW, and CMA are then created using the average of the two (small and big) top quantile CBP minus the average of the two bottom quantile CBP. An SMB_{CBP} factor is then created for each CBP using the average of the three small portfolios minus the three big portfolios. The final SMB factor is the average of the three SMB_{CBP} factors. Additionally, we use MKTrf, defined as the sample (monthly) market return minus the risk-free interest rate.

Table 1. EMU+ moments and correlations in % per month. This table shows the descriptive statistics of our bank-specific factors, as well as commonly used risk factors in asset pricing. All factors (except dCDSS) are calculated from the sample data June 1999 to June 2020. The descriptive statistics of the dCDSS cover the shorter period from January 2008 to June 2020.

	MKTrf	BANK	BMMkt	dCDSS	SMB	HML	RMW	CMA
Moments								
Mean	0.41	0.00	-0.43	1.62	0.11	0.35	0.39	0.29
Median	0.89	0.02	-0.20	-2.18	0.23	0.36	0.22	0.19
SD	4.04	0.19	3.82	17.48	2.44	2.74	1.62	1.98
Skewness	-0.58	-2.53	0.28	1.07	-0.55	0.24	0.53	0.90
Kurtosis	3.76	20.42	6.86	4.71	4.67	10.39	5.06	6.26
Cross-correlations in %								
MKTrf	100	59.76	26.27	-55.25	4.72	-13.05	-13.20	-39.43
BANK	59.76	100	57.23	-48.83	28.99	12.88	-21.92	-13.47
BMMkt	26.27	57.23	100	-40.23	31.15	36.46	-35.47	8.03
dCDSS	-55.25	-48.83	-40.23	100	-9.69	-37.05	42.92	7.23

Table 1 shows the summary statistics for the factors used in our analysis. BANK represents the monthly change of the banking sectors' overall DD (VWDD), as defined in Section 2.1. Therefore, its mean is zero, but it yields a high kurtosis of 20.42. This is in line with the factor created by Pereira and Rua (2018). This means that the values are concentrated around their mean, with distinct tails. When winsorizing, the kurtosis dramatically reduces to 4.68, which means the above high kurtosis may be a result of outliers. As we do not want to change the key characteristics (especially for the BANK factor), we refrain from generally winsorizing our factors; instead, we use this approach to check for robustness. The summary statistics for the winsorized TSF in the EMU+ dataset are reported in Table C1 in Appendix C.[7] There is a remarkable correlation between BANK and MKTrf. However, the correlation with SMB and HML is small.

BMMkt shows a negative mean, which is not surprising to those observing the European stock market over the past 20 years. A negative sign indicates the underperformance of banking shares compared to the market over the analysis period. The correlation with BANK is rather strong, which is expected, since both factors are connected via market value. Because of the much lower kurtosis and correlation with MKTrf, BMMkt could be a more sensible measure for the state of the banking sector and can potentially yield more information than BANK.

The dCDSS is at a different scale compared to the other factors, especially in terms

7. The summary statistics for the other datasets are available upon request.

of its mean and standard deviation. After the financial crisis, there was a sharp increase in CDS spreads (which never recovered). This is reflected by the average 1.62% monthly increase over the analyzed 12.5 years. Furthermore, dCDSS has a strong negative correlation with MKTrf, BANK, and BMMkt. This is as expected, since an increase in (banks') spreads indicates times of relative distress in the banking sector and/or generally.

3. Data

We use daily[8] and monthly total return data, as well as yearly accounting data from Datastream and Worldscope for our analysis. For an analysis period from June 1999 to June 2020, we need to start collecting data from 1993 onward. Considering the calculation of DDs, we need one year of data in advance. We lose further five years to perform varying β estimates with 60-months rolling windows, as described in Section 4. Unless otherwise indicated, we use the 1-month EURIBOR rate or its predecessor—the 1-month ECU deposit rate—as the risk-free rate throughout the analysis. We incorporate Worldscope lists and (if available) dead lists, as well as research lists for each country in the sample. This is done to mitigate a potential survivorship bias, as those lists include already liquidated companies. This resulted in 61,893 Datastream items for our EMU+ dataset. A full country list, including the used data items and a description of their usage in the analysis, can be found in Table A1 in Appendix A.

The data are retrieved in €, except for the UK and Switzerland, for which we initially retrieved data in their domestic currencies for the DD calculations. We applied several static filters to clean our data, following Ince and Porter (2006), Schmidt et al. (2019), Hanauer and Huber (2018), and others. All used static filters are summarized in Table B1 in Appendix B. We filter our data and convert the local currencies of the UK and Switzerland to € before merging them into the regional datasets (EMU+, EMU, EMU+ ex DE, and EMU ex DE). Accounting data are converted using the exchange rate on the respective fiscal year end. For other data, such as market value, we

8. Daily data are only used for the calculation of DDs.

convert the data based on daily reported exchange rates. After applying these filters, the EMU+ dataset reduces to 9,933 analyzable stocks over the analysis period. This reduction is mainly driven by filter #4, as defined in Table B1 in Appendix B, which requires the ISIN of a company to be the primary listing. The country composition of the EMU+ dataset is shown in Figure A1 in Appendix A. In addition to these static filters, we also apply dynamic filters, where stocks are not excluded as a whole, but temporarily e.g. for so-called penny stocks. The rules for those dynamic filters are defined in Table B2 in Appendix B. These dynamic filters further reduce (periodically) the number of analyzable stocks. The average number in our cross-sectional regressions, as described in chapter 5.3, is around 3,000 (non-financial) companies per month in the EMU+ dataset, depending on the calculated model and the availability of its regressors.

We calculate the DDs using country-specific interest rates before a country starts being part of the EMU. Subsequently, we use the 1-year EURIBOR. By doing so, we account for potentially different monetary policies in the member states before joining the Eurozone when calculating the DDs. All interest rates utilized in our study are outlined in Table A2 in Appendix A. For the UK and Switzerland, we perform DD calculations—as well as calculations on the investment and profitability factors—in their domestic currencies. We follow Pereira and Rua (2018) and use only the DDs of stocks with SIC codes between 6020 and 6036 for the calculation of BANK. We identify 317 banking institutions in our EMU+ sample. On average, 149 DDs of banking institutions are used per month to calculate BANK. Figure A2 in Appendix A shows the 10 banks with the highest average weight in BANK. We choose the 'Short Term Debt & Current Portion Of Long Term Debt' from Worldscope as a proxy for the value of debt due in one year ($F_{i,t+1}$). This matches the definition of the Worldscope item.

For the calculation of dCDSS, we use the monthly percentage change in the 'DS Europe Banks 5Y CDS Index €', as provided by Datastream. As outlined by Longstaff, Mithal, and Neis (2005), Bhat, Callen, and Segal (2014), or Chen and Chen (2018) contracts with a 5-year maturity are the most common and most liquid. Therefore, we extend our analysis by using the monthly change in the above mentioned CDS index. Since data are only available from December 2007 onward, the analysis based on this index has been conducted for a shortened period, from January 2013 to June 2020.

4. Asset pricing tests

This section describes the asset-pricing tests performed in this study. The test assets consist of the EMU+, EMU, EMU+ ex DE, EMU ex DE datasets, as well as UK and DE only, always excluding stocks with SIC codes between 6000 and 6999.

Spanning regressions

As outlined by Fama and French (2017) spanning regressions can indicate a risk premium in excess of other known risk factors. This is done by regressing the candidate factors on other factors, potentially explaining the cross-section of stock returns. If there is a significant intercept in those regressions, the candidate factor contains a return pattern, which is not absorbed by the established factors and might thus add value to the model. We use the TSF from the FF-5 model, namely SMB, HML, RMW, and CMA, as controls for our bank-specific factors. As Fama and French (1993) already stated, the value factor may contain information related to the distress of a company. Therefore, the used risk factors (e.g., HML) may have similar information, captured by our bank-specific risk factors.

Since BANK and dCDSS are macroeconomic variables, they do not express a risk premium return pattern (in contrast to BMMkt and the other TSF) as needed for the spanning regressions. The interpretation of the results using such macroeconomic variables would be thus very limited. As such, we create factor-mimicking portfolios for BANK and dCDSS and use them in our spanning regressions. We use a 5-year rolling window regression approach to generate monthly BANK-βs and dCDSS-βs. Each month, we sort our stocks according to their exposure to those coefficients, using the 30% and 70% quantile breakpoints of big stocks. After calculating the value-weighted portfolio returns, we create our monthly time series of long-short portfolios, ‘High BANK minus Low BANK’ (HBMLB) and ‘High dCDSS minus Low dCDSS’ (HCMLC).

The results of the spanning regressions should be handled carefully. As outlined by Harvey and Liu (2021), factors that ‘pass’ such spanning tests may yield additional information, but still not be helpful in explaining the cross-section of stock returns. When using individual stocks, as we do in our analysis, this is even more relevant.

Portfolio sorts

Portfolio sorting is a widely used approach to determine whether a factor is indeed a priced factor in the cross-section of stock returns. If a factor yields a relevant influence, a distinct return pattern between the sorted portfolios should become visible. Factor exposure is calculated in 60-months rolling TSRs of individual stocks’ excess returns on MKTrf, BANK, BMMkt, and dCDSS. We require a minimum of 18 valid return observations (30%) within the 60-month window to calculate these βs. For single-sorted portfolios based on the exposure to only one factor, we use lagged betas from univariate TSRs, as in equation (6). For double-sorted portfolios based on the exposure to two factors, we use lagged betas from bivariate TSRs, as in equation (7):

$$R_{i,t} - rf_t = \alpha_i + \beta_{i,b,t} f_{t,b} + \epsilon_{i,t}, \tag{6}$$

$$R_{i,t} - rf_t = \alpha_i + \beta_{i,b,t} f_{t,b} + \beta_{i,m,t} MKTrf_t + \epsilon_{i,t}, \tag{7}$$

where $R_{i,t}$ is the return of the individual stocks at time t, rf_t is the risk-free-rate at time t, MKTrf is the market excess return, and $f_{t,b}$ is the respective bank-specific risk factor at time t.

Depending on the factor exposures of each stock, they are grouped monthly into five portfolios, from low to high exposure to each factor, as expressed by the lagged beta coefficient, $\beta_{i,b,t-1}$. We use beta coefficients lagged by one month to avoid a lookahead bias. The double-sorted portfolios are created using the intersections between the portfolios sorted on $\beta_{i,m,t-1}$ and $\beta_{i,b,t-1}$, resulting in 25 independently sorted portfolios. We then calculate the market value-weighted portfolio returns for each uni- and bivariately sorted portfolio.

Fama–MacBeth regressions

Our main asset pricing tests consist of a series of regressions based on the Fama and MacBeth (1973) procedure (FMB). First, we implement a model using time-varying βs (factor loadings), as derived from equation (7), with 60-months rolling windows. These are then used in the second-stage cross-sectional regressions (CSR), as in equation (8):

$$R_{i,t+1} - rf_{t+1} = \alpha_{t+1} + \lambda_{t+1,b}\beta_{i,t,b} + \lambda_{t+1,m}\beta_{i,t,m} + CC_i + \epsilon_{t+1}, \tag{8}$$

where CC is a dummy variable that accounts for country-specific effects. λs are factor risk premiums.

In the second step, to mitigate the omitted variable bias (OVB), we include factor loadings on the TSF of the FF-5 model, as in Chordia, Goyal, and Shanken (2015). To do so, we run another series of first-stage time-series regressions with 60-months rolling windows using equation (9) to commonly estimate all βs used in the CSR, as in equation (10):

$$R_{i,t} - rf_t = \alpha_{i,t} + \beta_{i,b,t}f_{t,b} + \beta_{i,m,t}MKTrf_t + \sum_{tsf}\beta_{i,t,tsf}f_{t,tsf} + \epsilon_{i,t}, \tag{9}$$

$$
\begin{aligned}
R_{i,t+1} - rf_{t+1} = \alpha_{t+1} + \lambda_{t+1,b}\beta_{i,t,b} + \lambda_{t+1,m}\beta_{i,t,m} \\
+ \sum_{tsf} \lambda_{t+1,tsf}\beta_{i,t,tsf} + CC + \epsilon_{t+1},
\end{aligned}
\tag{10}
$$

where $f_{t,tsf}$ represents size risk premium SMB, value premium HML, profitability premium CMW, and investment premium RMW and $\beta_{i,tsf,t}$ are the factor loadings for each stock on the TSF.

As Chordia, Goyal, and Shanken (2015) argue, stock-specific time-varying variables might be better suited to increase the explanatory power of CSRs compared to β-based variables. Therefore, we integrate these characteristics into our CSRs as a final step. Equation (11) augments equation (10) with the corresponding stock characteristics to the used TSF, namely ln(size), ln(BM), CbGP, and Inv:

$$
\begin{aligned}
R_{i,t+1} - rf_{t+1} = \alpha_{t+1} + \lambda_{t+1,b}\beta_{i,t,b} + \lambda_{t+1,m}\beta_{i,t,m} \\
+ \sum_{tsf} \lambda_{t+1,tsf}\beta_{i,t,tsf} + \sum_{char} \lambda_{t+1,char} f_{i,t,char} + CC + \epsilon_{t+1},
\end{aligned}
\tag{11}
$$

where $f_{i,t,char}$ are the described characteristics and $\lambda_{t+1,char}$ is the corresponding premium.

As a robustness check, we calculate factor loadings $\beta_{i,tsf,t}$ winsorized (at the 1% and 99% levels) and unwinsorized TSF for each country composition separately using equation (9).

In our FMB regressions, we use individual stocks. A growing strand of the literature advocates the use of individual stocks. For instance, Ang, Liu, and Schwarz (2020) recommend their usage instead of portfolios, since the aggregation leads to a loss of information. They show that portfolio construction does not translate into lower standard errors of the factor risk premiums, which is one of the main motivations for portfolio usage. By comparing the performance of time-series and cross-sectional models, Fama and French (2020) find that the latter ones perform better when time varying characteristics are analyzed. Jacobs and Levy (2021) also highlight the benefits of cross-sectional models and the possibility to focus on individual stocks. They state that practitioners are interested in '[...] understanding and predicting the cross-sectional differences in expected returns of individual stocks' (p. 12). Harvey and Liu (2021) argue that the identification of factors is highly dependent on the determinants used in the portfolio creation process. They conclude that, although portfolio creation reduces idiosyncratic noise, they should ideally not be used in asset pricing tests. Therefore, we consider individual stocks, which also enables us to include country dummies. However, there are two major drawbacks to using individual stocks. First, individual stocks are much noisier than the portfolio approach, leading to a low R^2s in the regression analysis. Second, because the βs used as explanatory variables in our CSRs are estimated in first-stage TSRs, we have to deal with the error-in-variables (EIV) bias. Owing to this bias, the coefficient estimates may be biased toward zero (attenuation bias). This measurement error also has side effects on the other estimates in the CSRs, known as the contamination bias, as outlined by Collot and Hemauer (2021). Because we have more than one estimated β in our regressions, the direction of these two biases combined is not determinable.

Since cross-sectional analysis experiences a comeback, recent studies have proposed methods to deal with the EIV bias. For example, Jegadeesh et al. (2019) take advantage of instrumental variables (IV) procedures, using the two-stage least squares method (2SLS) to account for the biased β estimates. They start by calculating βs for even and odd months separately, using daily return data. In even months, 'even βs' are used in the CSR as explanatory variables (EV) and 'odd βs' as IV. In the odd months, the assignment switches. We refrain from using this approach to deal with the EIV bias in our analysis, as our data have (in contrast to those of Jegadeesh et al. (2019)) monthly periodicity. Generating rolling βs with reasonable window lengths would thus lead to imprecise β estimates in our setting.

Chordia, Goyal, and Shanken (2015) propose a more direct procedure to correct the

EIV bias. They collect the White (1980) variance-covariance matrices of the estimated βs from the first stage TSR and use them to correct the OLS 'denominator'. The approach of using second order moments of the errors to correct the EIV bias was already proposed by Theil (1971), further developed by Shanken (1992), and refined to be used in FMB regressions with individual stocks by Chordia, Goyal, and Shanken (2015). To account for the EIV bias, we use their proposed procedure. EIV-corrected coefficients γ_{t+1}^{EIV} are calculated (in the case of equation (10)) using equation (12):

$$\gamma_{t+1}^{EIV} = (\hat{X}_t' \hat{X}_t - \sum_{i=1}^{N_t} M' \hat{\Sigma}_i M)^{-1} \hat{X}_t' Y_{t+1}, \tag{12}$$

where $\hat{X}_t$ has an $n \times (1 + k + k_2)$ structure, k is the number of estimated βs, and k_2 is the number of other variables, such as country control variables. $\hat{\Sigma}_i$ are the $k \times k$ White (1980) variance–covariance matrices from the first-stage TSR. Following Chordia, Goyal, and Shanken (2015), before summing up the elements of these variance-covariance matrices, we winsorize element-wise at the 1% and 99% levels to eliminate outliers. M is a $k \times (1 + k + k_2)$ matrix, with a $[0\ I\ 0]$ structure, used to scale $\hat{\Sigma}_i$. Y_{t+1} is the vector of the realized excess returns of each stock in the cross-section at month t+1.

Thus far, the correction term in equation (12) is used in our analysis and has the following form, as long as no price-related time-varying stock characteristics are considered (as in equation (10)):

$$\sum_{i=1}^{N_t} M' \hat{\Sigma}_i M = \sum_{i=1}^{N_t} \begin{bmatrix} 0_{1\text{x}1} & 0_{1\text{x}k} & 0_{1\text{x}k_2} \\ 0_{k\text{x}1} & \hat{\mathbf{\Sigma}}_{\mathbf{i}} & 0_{k\text{x}k_2} \\ 0_{k_2\text{x}1} & 0_{k_2\text{x}k} & 0_{k_2\text{x}k_2}. \end{bmatrix} \tag{13}$$

Chordia, Goyal, and Shanken (2015) acknowledge that this procedure might be troublesome in certain situations. We follow their approach and switch to the OLS estimator in case implausible results are observed in the CSR for a specific month. This is when matrix $\hat{X}_t'\hat{X}_t - \sum_{i=1}^{N_t} M'\hat{\Sigma}_i M$ is not positive definite and, thus, not invertible or close to zero. In the latter case, we switch to the OLS estimator when the absolute difference between the calculated β premium and its corresponding time series factor is above 20%.

As stated by Chordia, Goyal, and Shanken (2015), an additional bias may arise when price-related time-varying characteristics Z are used as additional explanatory variables in CSRs, as in equation (11). This is due to the fact that the estimation errors in the βs may be correlated with those characteristics. In such case, another correction factor, cf_Z, must be added to equation (13) to account for this issue. This is given by Equation (14):

$$cf_{Z,i,t} = (F_d'F_d)^{-1} \sum_s \rho_i^{t-s} F_{d,s}' \epsilon_{i,s} \nu_{i,s}, \tag{14}$$

where F_d is the de-meaned matrix of the TSFs in equation (9), $\epsilon_{i,s}$ are stock-specific residuals from these regressions, and s is a time index representing the months within the rolling window. ρ^{t-s} and $\nu_{i,s}$ are obtained from the stationary AR(1)representation of the price-related time-varying characteristics, as in equation (15):

$$Z_{i,s} - \overline{Z}_i = \rho_i(Z_{i,s-1} - \overline{Z}_i) + \nu_{i,s}, \tag{15}$$

where Z_i is the price-related time-varying characteristic and $\overline{Z_i}$ is the arithmetic mean of Z_i within the rolling window. The correction factor is calculated separately for each characteristic Z. The derivation of this correction term is described in detail in Appendix 1 in Chordia, Goyal, and Shanken (2015). The final EIV-corrected coefficients with price-related time-varying characteristics are given by equation (16):

$$\gamma_{t+1}^{EIV} = \left(\hat{X}_t' \hat{X}_t - \sum_{i=1}^{N_t} \begin{bmatrix} 0_{1\text{x}1} & 0_{1\text{x}k} & 0_{1\text{x}k_c} & 0_{1\text{x}k_2} \\ 0_{k\text{x}1} & \hat{\mathbf{\Sigma}}_{\mathbf{i},\mathbf{t}} & 0_{k\text{x}k_c} & 0_{k\text{x}k_2} \\ 0_{k_c\text{x}1} & \mathbf{cf}_{\mathbf{Z},\mathbf{i},\mathbf{t}} & 0_{k_c\text{x}k_c} & 0_{k_c\text{x}k_2} \\ 0_{k_2\text{x}1} & 0_{k_2\text{x}k} & 0_{k_2\text{x}k_c} & 0_{k_2\text{x}k_2} \end{bmatrix} \right)^{-1} \hat{X}_t' Y_{t+1}, \tag{16}$$

where k_c is the number of price-related time-varying characteristics that are corrected. This augmented correction is used in Section 5.3 for those models using (the natural log of) size and BM[9] as regressors, with market value as a direct priced-based component. As our estimations have a monthly periodicity, we impose a data availability on these factors of at least 90% to obtain reliable AR(1) coefficients. Since investment and profitability are not directly price-based, we follow Chordia, Goyal, and Shanken (2015), and refrain from any correction on those variables. Therefore, these two factors are considered constituents of k_2.

We obtain the average regression coefficients, as well as their (Newey and West (1987)) standard deviations by regressing the resulting time series of the cross-sectional estimates (γ^{EIV}) on a constant.

5. Results

We perform several tests to understand how the banking sector's state influences the cross-section of stock returns. We describe below in detail the results using the EMU+ dataset, unless indicated otherwise. Further analyses on the other mentioned datasets are available upon request.

5.1. Spanning regressions

Table 2 shows the results of our spanning regressions using the EMU+ dataset. The intercept of HCMLC is not significantly different from 0. This means that a poten-

9. For our FMB-regressions, the latest available market value is used as size factor, as well as for the calculation of the monthly BM factor. We use the book value of year t-2 until May each year. From June onward, we use the book value from year t-1.

tial risk-premium based on the exposure to dCDSS is already captured by the FF-5 factors. However, BMMkt generates a significant monthly α of -0.6878%, with a corresponding (absolute) t-value of 3.36, which cannot be explained by the FF-5 factors. This is economically highly relevant, especially when considering that BMMkt is a long-short portfolio. This means, by changing the assignment and going long into the market and short in banks, an investor might be able to outperform the FF-5 model. The significance of the α of BMMkt is robust, in that we observe t-values across all country compositions and also when using winsorized factors of around 3 or higher. The long-short strategy on the exposure of stocks to BANK (HBMLB) generates an insignificant α of -0.3272% per month. However, in the datasets excluding the UK and Switzerland, the αs further decrease to -0.4837 (EMU) or -0.4741 (EMU ex DE), both with (absolute) t-values of about 2.15. Therefore, in those datasets, an uncaptured risk-premium based on the exposure to BANK might exist.

The presented spanning regressions are only a first indication whether our banks' individual factors yield additional information compared to other already existing factors. Hitherto, the most promising candidate seems BMMkt.

Table 2. EMU+ spanning regressions in % per month of form $f_b = \alpha + \beta_m MKTrf + \beta_s SMB + \beta_h HML + \beta_r RMW + \beta_c CMA + \epsilon$, where f_b are the long-short portfolios BMMkt, HBMLB, or HCMLC. We report the absolute t-values to H_0—the coefficient is indistinguishable from 0—between parentheses. The sample period used in the spanning regressions for HBMLB and BMMkt is from June 1999 to June 2020 and for HCMLC from January 2013 to June 2020.

	HBMLB	BMMkt	HCMLC
α	-0.3272	-0.6878	0.0889
	(1.4178)	(3.3565)	(0.4688)
MKTrf	0.6760	0.3734	-0.3123
	(12.549)	(7.8051)	(5.8772)
SMB	0.1892	0.3788	-0.3833
	(2.1107)	(4.7586)	(4.2121)
HML	-0.0858	0.3871	-0.6622
	(0.6566)	(3.3365)	(3.8223)
RMW	0.1033	-0.2141	0.1139
	(0.5906)	(1.3781)	(0.5418)
CMA	-0.2483	0.1551	-0.0046
	(1.5006)	(1.0555)	(0.0245)
R^2	0.4815	0.3945	0.6920
Adj. R^2	0.4710	0.3823	0.6737

5.2. Portfolio sorts

BANK

Panel A of Table 3 shows the single-sorted portfolio returns for portfolios sorted on the BANK-β in the EMU+ dataset. An expected monotonically increasing return pattern is not observed. In fact, there seems to be no return pattern. Looking at the double-sorted portfolios on the βs of MKTrf and BANK, as in Panel B, there is also no observable effect, depending on market exposure. This is valid across all analyzed datasets and can be seen as another indication that BANK has no explanatory power for the expected returns in the samples' cross-section. The results contradict the evidence from the US market, as reported by Pereira and Rua (2018), where there is a distinct pattern observable, especially in the single-sorted portfolios on BANK-βs.

Table 3. EMU+ portfolio returns for sorted portfolios on BANK-βs. This table shows the average excess returns of each single or double-sorted portfolio in % per month. The single-sorted portfolios are created using time-varying univariate BANK-βs from equation (6), whereas the double-sorted portfolios are based on the bivariate βs from equation (7). Hi-Lo indicates the return difference between the highest-ranked BANK-β portfolios and the lowest-ranked BANK-β portfolios. The corresponding t-stat is represented as an absolute value (H_0: Hi-Lo equals zero). The portfolios are created from June 1999 to June 2020. Firms with SIC codes between 6000 and 6999 are excluded.

Panel A: Single-sorted portfolios on BANK-βs							
Quintiles	BANK1	BANK2	BANK3	BANK4	BANK5	Hi-Lo	|t-stat|
Returns	0.609	0.362	0.466	0.518	0.357	-0.253	0.655

Panel B: Double-sorted portfolios on MKTrf- and BANK-βs							
Quintiles	BANK1	BANK2	BANK3	BANK4	BANK5	Hi-Lo	|t-stat|
MKTrf1	0.241	0.439	0.545	0.589	0.153	-0.088	0.159
MKTrf2	0.680	0.596	0.478	0.652	0.609	-0.070	0.165
MKTrf3	0.601	0.647	0.668	0.582	0.324	-0.277	0.674
MKTrf4	0.326	0.217	0.817	0.454	0.407	0.081	0.204
MKTrf5	0.013	0.342	0.463	0.755	0.474	0.461	0.979

Bank spread factor (BMMkt)

Table 4 shows the pattern of expected returns for the EMU+ dataset when sorted according to their exposure to BMMkt. The single-sorted portfolios on BMMkt (Panel A) have a distinct return pattern, in contrast to the BANK based portfolios. Comparing the average excess returns of the lowest and the highest-ranked portfolio, there is a considerable difference of 0.601% per month, with a t-value of 1.691, which might even be considered significant at a low significance level. When excluding the UK and Switzerland from the sample by using the EMU dataset, the return difference increases to 0.853% per month, with a t-stat of 2.661. When we exclude German stocks (EMU ex DE), the return difference drops to 0.583%, with a t-stat of 1.750. It seems that German companies react more sensibly to BMMkt compared to other companies in the sample. To isolate this effect, we perform a similar analysis using German stocks only. Since this sub-sample is much smaller, we reduce the number of portfolios to 16. Table D1 in Appendix D shows the results for DE only. In Panel A, we indeed find a monotonically increasing return pattern. However, the return difference with a t-value of 1.515 is not significant. We follow up this issue in the Fama–MacBeth regressions in the next section.

The double-sorted portfolios on BMMkt (Panel B) on the EMU+ dataset show no distinct pattern in terms of monotonically increasing returns. In terms of the return difference between the portfolio with the highest exposure to BMMkt and the lowest-ranked portfolio, we only find significant results for those portfolios with the highest MKTrf-β. However, this effect is not robust to sample variations.

Table 4. EMU+ portfolio returns for sorted portfolios on BMMkt-βs. This table shows the average excess returns of each single- or double-sorted portfolio in % per month. The single-sorted portfolios are created using the time-varying univariate BMMkt-βs from equation (6), whereas the double-sorted portfolios are based on the bivariate βs from equation (7). Hi-Lo indicates the return difference between the highest-ranked BMMkt-β portfolios and the lowest-ranked BMMkt-β portfolios. The corresponding t-stat is represented as an absolute value (H_0: Hi-Lo equals zero). The portfolios are created from June 1999 to June 2020. Firms with SIC codes between 6000 and 6999 are excluded.

Panel A: Single-sorted portfolios on BMMkt-βs							
Quintiles	BMMkt1	BMMkt2	BMMkt3	BMMkt4	BMMkt5	Hi-Lo	|t-stat|
Returns	0.111	0.151	0.445	0.525	0.711	0.601	1.691
Panel B: Double-sorted portfolios on MKTrf- and BMMkt-βs							
Quintiles	BMMkt1	BMMkt2	BMMkt3	BMMkt4	BMMkt5	Hi-Lo	|t-stat|
MKTrf1	0.343	-0.163	0.594	1.085	0.703	0.360	0.466
MKTrf2	-0.061	0.411	0.647	0.588	0.586	0.647	1.460
MKTrf3	0.412	0.438	0.232	0.564	0.310	-0.103	0.267
MKTrf4	0.604	0.324	0.699	0.615	0.687	0.083	0.248
MKTrf5	-0.014	0.367	0.362	0.457	0.801	0.815	2.399

Change of the bank-based Credit Default Swap Spread Index (dCDSS)

Owing to the shorter availability of CDS data, the expected return pattern presented in Table 5 covers only the period from January 2013 to June 2020. The data provide no recognizable pattern for the portfolios sorted on the exposure to the monthly change in the CDS index. This is valid for single-sorted portfolios, as shown in Panel A, as well as for the double-sorted portfolios in Panel B and across all other analyzed datasets.

The return difference between the highest-ranked and lowest-ranked portfolios is also insignificant. Moreover, we observe sign changes among the single- and double-sorted portfolios Hi-Lo, depending on the market exposure and dataset used. This indicates that exposure to dCDSS has no influence on the return patterns of non-financials, supporting our spanning regression results in the previous section.

Table 5. EMU+ portfolio returns for sorted portfolios on dCDSS-βs. This table shows the average excess returns of each single or double-sorted portfolio in % per month for the EMU+ dataset. The single-sorted portfolios are created using the time-varying univariate dCDSS-βs from equation (6), whereas the double-sorted portfolios are based on the bivariate βs from equation (7). Hi-Lo indicates the return difference between the highest-ranked dCDSS-β portfolios and the lowest-ranked dCDSS-β portfolios. The corresponding t-stat is represented as an absolute value (H_0: Hi-Lo equals zero). The portfolios are created from January 2013 to June 2020. Firms with SIC codes between 6000 and 6999 are excluded.

Panel A: Single-sorted portfolios on dCDSS-βs							
Quintiles	dCDSS1	dCDSS2	dCDSS3	dCDSS4	dCDSS5	Hi-Lo	|t-stat|
Returns	0.765	0.582	0.831	0.787	0.655	-0.110	0.266

Panel B: Double-sorted portfolios on MKTrf- and dCDSS-βs							
Quintiles	dCDSS1	dCDSS2	dCDSS3	dCDSS4	dCDSS5	Hi-Lo	|t-stat|
MKTrf1	1.059	1.165	0.388	0.517	-0.390	-1.449	1.655
MKTrf2	1.230	0.965	0.970	0.487	0.603	-0.627	0.845
MKTrf3	0.769	1.034	0.737	0.855	0.923	0.154	0.281
MKTrf4	1.802	0.827	0.650	0.676	0.896	-0.906	1.772
MKTrf5	0.259	0.210	0.652	1.223	0.548	0.289	0.461

Thus far, from the perspective of sorted portfolios, BMMkt seems best suited as a bank-based risk factor to explain the influence of banking stability on the cross-section of non-financial stock returns.

5.3. Fama–MacBeth regressions

We calculated a total of 216 FMB models[10] to check the robustness of the results. Table 6 shows the results of our FMB-regressions for EMU+ using BMMkt-β as the bank individual factor. Despite being the most promising bank individual factor in the preceding analysis, we see no effect in our FMB regressions. The magnitude of -0.09 to 0.08 is economically irrelevant, all corresponding t-values are below 1, and the sign even switches. As mentioned in the previous section, BMMkt might affect German stocks. Table E2 in Appendix E reports the results for the German stock market

10. That is, three bank individual factors and six models (three OLS and three EIV) using winsorized and unwinsorized TSF for the following country compositions: EMU+, EMU, EMU+ ex DE, EMU ex DE, DE only, and UK only.

only. In the OLS regressions, we observe economically relevant factor risk premiums of 0.27%—0.49% per month on the BMMkt-β, with t-values between 1.7617 and 2.3926. However, when using winsorized factors, the factor risk premiums reduce to 0.23%—0.45%, with corresponding t-values of 1.6525—2.2206. Furthermore, this significance vanishes in the EIV regressions. Since the observed levels of significance are not fully convincing and do not hold, when correcting for the EIV bias, we do not consider those observed effects as proof of relevant spillover-effects in Germany. Moreover, the effects of BMMkt-β on the German subsample are the best. We do not observe other significant results in our different analyzed sample compositions using BMMkt-β.

Table 6. EMU+ Fama–MacBeth regression results using BMMkt-βs. This table shows time series averages in % per month of the cross-sectional OLS estimates based on equations (10) and (11), as well as the EIV corrected estimates following Chordia, Goyal, and Shanken (2015) and equations (12) and (16). Firms with SIC codes between 6000 and 6999 are excluded. We control for country effects using dummy variables. We report the absolute t-values (based on Newey–West standard errors) to H_0—the coefficient is indistinguishable from 0—between parentheses. CSRs were performed each month from June 1999 to June 2020.

	OLS1	OLS2	OLS3	EIV1	EIV2	EIV3
Intercept	0.69**	0.64**	0.46	0.82***	0.58**	0.43
	(2.3818)	(2.2677)	(1.3089)	(3.1244)	(2.2447)	(0.923)
BMMkt-β	0.08	0.07	0.02	0.04	-0.09	0.03
	(0.9409)	(0.8723)	(0.2895)	(0.2122)	(0.4873)	(0.1355)
MKTrf-β	-0.13	-0.09	-0.08	-0.37	-0.21	-0.40
	(0.9287)	(0.7839)	(0.5462)	(1.5511)	(1.044)	(1.1066)
SMB-β		0.06	0.04		0.16	0.14
		(1.149)	(0.8433)		(1.562)	(0.8232)
HML-β		0.14	0.15		0.24	0.02
		(1.4315)	(1.6063)		(1.3818)	(0.0906)
CMA-β		0.06	0.07		0.10	0.15
		(0.8048)	(0.9256)		(0.7153)	(0.9966)
RMW-β		-0.03	-0.01		-0.02	0.19
		(0.8825)	(0.3369)		(0.2217)	(1.172)
ln(Size)			0.00			0.05
			(0.0854)			(0.5269)
ln(BM)			0.11			0.13
			(1.2259)			(0.5534)
CbGP			0.69***			0.57***
			(6.1315)			(3.6158)
Inv			-0.01			-0.06
			(0.8198)			(1.0464)
R^2	0.0424	0.05	0.0616			
Adj. R^2	0.0353	0.0417	0.0514			
n	3014.5929	3014.5929	2599.6957	3014.5929	3014.5929	2054.6759

For those models using BANK-βs as bank individual factor, we observe some statistical significance in the EMU+ ex DE sample, but all of them are economically irrelevant because the absolute magnitude of the premium stays well below 0.1 and even switches signs. Recalling the definition of BANK, a regression coefficient of 0.1

means that an increase (decrease) in VWDD of 1 within 1 month leads to a higher (lower) monthly stock performance of only 0.1%. This confirms our observations and interpretations of the preceding asset-pricing tests.

dCDSS-β performs slightly better in this respect, especially in the datasets where Germany is overrepresented (EMU and DE). Using the EMU sub-sample, we find significant risk premiums for the dCDSS-β exposure in the OLS3 and EIV3 models at low significance levels. They might also be considered economically relevant, with magnitudes of -0.97 (OLS3) or -2.85 (EIV3) and corresponding t-values of 1.9253 and 2.4383, respectively. Moreover, the signs are as expected, and the described effects remain when using the β from the winsorized version of the dCDSS. However, the effect is not robust against model variations (the other four OLS and EIV models of EMU are all insignificant) or across different sample compositions.

Generally, the TSF and their corresponding βs do a poor job of explaining the cross-section of stock returns of individual stocks in our sample. This is in line with Chordia, Goyal, and Shanken (2015). There are some models in which we can observe a significant factor risk premium (e.g., the HML-β in the EMU ex DE sample with BMMkt shows significant magnitudes of 0.16 (OLS2) and 0.62 (EIV2) with corresponding t-values of 1.7748 or 2.2919 respectively), but they are not stable for the different models and country compositions used. Regarding the characteristics, the CbGP of Hanauer and Huber (2018) can be considered a priced factor in our sample. This is because it exhibits an economically relevant and statistically significant factor risk premium in almost any analyzed model, despite the presence of its corresponding TSF in the CSRs. We find no evidence of a stable size, value or investment premium in our sample (Irrespective of using the natural log of BM or BM directly). This is in line with the findings of Dirkx and Peter (2020) and Artmann et al. (2012), who found no proof of these premiums, at least for the German market. Dirkx and Peter (2020) do not find a profitability premium as well, as opposed to our analysis. This might be due to the different profitability measure in our study.

Considering the different sample compositions used, as well as the various asset pricing tests performed, we provide highly robust results regarding the irrelevance of our bank individual risk factors on the cross-section of non-financial companies. There might be several reasons why the BANK-factor, as proposed by Pereira and Rua (2018), as well as all other discussed bank individual risk factors do not work in our analyzed samples. First, our analysis covers only a short period since the establishment of the European Monetary Union. Therefore, we cannot observe the effects present in the 1960s–1990s, when banks might have played a more important role than over the past two centuries. Pereira and Rua (2018) cover this longer period. Second, there are different regulatory frameworks between the US and the EMU, which might mitigate the effects of distress in the banking sector to spillover to the cross-section of stocks belonging to the so-called 'real economy.' Third, US banks are more active in stock markets, in contrast to their European counterparts. As such, in times of distress in the banking sector, they might not be able to freely act on the stock market. This limits their room for action and translates on the return patterns of non-financial stocks. Finally, from a historical viewpoint, European banks have often been bailed out by governmental interventions to prevent systemic shocks and mitigate the effects of banking crisis on the real economy. The two most prominent examples are the German Commerzbank AG and the Italian Monte dei Paschi di Siena S.p.A. For this reason, those investing in the European Union might react rather insensibly when it comes to a worsening of the health of the banking system.

6. Discussion and Conclusions

In this study, we examine the importance of a healthy banking sector for the European stock market. For this purpose, we use data from all countries of the EMU, Switzerland, and the United Kingdom. We follow Pereira and Rua (2018) and create BANK, a bank-specific risk factor based on the VWDD of companies whose businesses mainly depend on lending activities. Moreover, we use two additional variables—a long-short portfolio of banking shares minus the market portfolio and the monthly change rate of an index representing the average CDS spread in the banking community in Europe—to proxy the health of the European banking sector.

Given these potential factors, we perform several asset pricing tests, consisting of spanning regressions, uni- and bivariate portfolio sorts, and FMB regressions on different test asset combinations. To account for the EIV bias in our FMB regressions, in addition to the traditional OLS coefficients, we calculate EIV-corrected values, as proposed by Chordia, Goyal, and Shanken (2015), taking advantage of the variance-covariance matrices from the first-stage TSRs.

There are some limitations in our study design. The choice to consider the European market has some drawbacks. The most obvious one is data availability, since from a historical viewpoint, Europe cannot be seen as a single market. By applying 60-months rolling windows to calculate the required factor loadings, data from before the foundation of the EMU in 1999 have to be considered over a reasonable analysis period.

Our results provide no evidence that the health of the banking sector influences the returns of non-financials in Europe. Is the health condition of banking institutions irrelevant for the return patterns on non-financials in Europe? To answer this question, further research is required. There are two main transition channels from a healthy banking sector to financial markets, which should be considered.

The first is mainly due to liquidity provisioning for market participants. It is possible that liquidity provisioning was more important in the years before the analysis period. Nowadays, there are several ways to acquire liquidity due to digitalization. Moreover, after the 2008 banking crisis, the European Central Bank reduced the fixed rate for its main refinancing operations and provided further liquidity to markets with its asset purchase programs. At the same time, stricter regulatory requirements were imposed, aiming at the prevention of systemic problems, as outlined in recital 5 of EU Directive 2014/65/EU (EU (2014)). Therefore, the health condition of banks may no longer be the determining factor in liquidity provisioning.

The second transition channel is due to financial market activities from the banking sector. A healthy banking sector has more possibilities to act on financial markets and, thus, exert influence on the stock returns of non-financials. The higher regulatory standards in Europe following the banking crisis in 2008 might have led to a reduction in operations in investment banking, weakening this transition channel.

In addition to these two transition channels, another effect should be considered. Market participants investing in European stocks might underestimate the danger of a sick banking sector. This could be due to (historical) extensive interventions to save banks from bankruptcy. The cases of the German Commerzbank AG and the Italian Monte dei Paschi di Siena S.p.A.—both backed by their respective governments—are well known to investors. Therefore, in combination with the above-mentioned EU Directive, investors might be less nervous when the health condition of the European banking sector is changing. The results of this study might also be interpreted as a moral hazard situation in Europe, where investors (as well as customers) enjoy free protection against systemic problems in the banking sector or as a (more or less) successful regulation of the European banking sector. Since this contrasts with the findings on the US, this paper can also serve as a basis for further research on the different roles banking systems have in the US and Europe. A deeper understanding of this field can contribute to a further examination of the ambivalent role that banks play in financial markets.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix A. Data items

Table A1. Countries and Datastream lists per country. Lists may be used in more than one country if companies in several countries are included in one list. The correct mapping of companies per country is ensured by the data screens, as described in B

Country	Country code	Lists
Austria	AT	WSCOPEOE, ALLAS, DEADOE, FOST
Belgium	BE	WSCOPEBG, DEADBG, FBEL
Cyprus	CY	WSCOPECP, DEADCY, FCYP
Estonia	EE	WSCOPEES, DEADES, FBIL, FBRCL, FSPDOM, FSPN, FSPNQ, FVAL
Finland	FI	WSCOPEFN, DEADFN, FFIN
France	FR	WSCOPEFR, ALLFF, DEADFR, FFDOM, FFOTC, FFRA
Germany	DE	WSCOPEBD, DEADBD1, DEADBD2, DEADBD3, DEADBD4, DEADBD5, DEADBD6, FGERDOM, FGERIBIS, FGKURS
Greece	GR	WSCOPEGR, DEADGR, FGREE, FGRMM, FGRPM, FNEX A
Ireland	IE	WSCOPEIR, DEADIR, FIRL
Italy	IT	WSCOPEIT, DEADIT, FITA
Latvia	LV	WSCOPELV, DEADLV, FLATA, FLATVIA
Lithuania	LT	WSCOPELN, DEADLT, FLATA, FLATVIA, LITHCM
Luxembourg	LU	WSCOPELX, FLUX
Malta	MT	WSCOPEMA, FMALTA, DEADML
Netherlands	NL	WSCOPENL, ALLFL, DEADNL, FHOL
Portugal	PT	WSCOPEPT, DEADPT, FPOR
Slovakia	SK	WSCOPESX, DEADSLO, FSLOVAK, FSLOVALL, ALLSLOV
Slovenia	SI	WSCOPESJ, DEADSV, FSLOVE
Spain	ES	WSCOPEES, DEADES, FBIL, FBRCL, FSPDOM, FSPN, FSPNQ, FVAL
United Kingdom	UK	WSCOPEUK, DEADUK, FBRIT, LSETSCOS, LSETSMM, LUKPLUSM, WSCOPEJE
Switzerland	SW	WSCOPESW, DEADSW, FSWA, FSWS

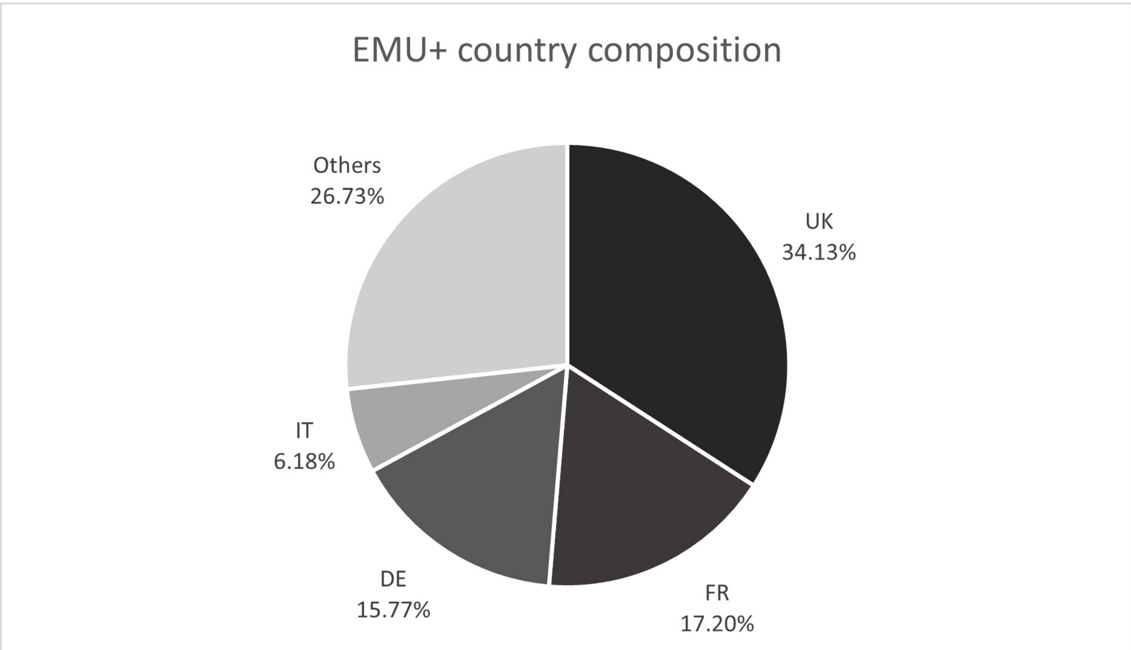

Figure A1. Country composition for the EMU+ dataset.

Table A2. Datastream and Worldscope items used. This table shows the Datastream and Worldscope items and their usage in our analysis. The periodicity indicates how the data were retrieved but not necessarily how they were used. For example, RI was retrieved with a daily periodicity and used on a daily basis for the creation of BANK. Our main analysis, however, was performed using RI with a monthly periodicity.

# Mnemonic	Usage	Periodicity
WC03040	ACCOUNTS PAYABLE: - Calculate cash-based gross profitability	y
WC03054	ACCRUED PAYROLL: - Calculate cash-based gross profitability	y
WC03501	COMMON SHAREHOLDERS EQUITY: - Calculate BM	y
WC01051	COST OF GOODS SOLD (EXCL DEP): - Calculate cash-based gross profitability	y
GEOGN	COUNTRY OF COMPANY: - Data screens	static
GEOLN	COUNTRY OF SECURITY: - Data screens	static
PCUR	CURRENCY SHORTCUT: - Data screens	static
WC03262	DEFERRED INCOME: - Calculate cash-based gross profitability	y
WC03263	DEFERRED TAXES: - Calculate BM	y
DSEBK5E	DS Europe Banks 5Y CDS Index €: - Creation of the dCDSS	m
EIBOR1M	EBF EURIBOR 1M DELAYED - OFFERED RATE: - Calculate excess returns	d
EIBOR1Y	EBF EURIBOR 12M DELAYED - OFFERED RATE: - Calculate DDs	d
ECUDP1M(IO)	ECU DEPOSIT 1 MONTH (LDN) - OFFERED RATE: - Calculate excess returns before 1999	d
EXNAME	EXCHANGE NAME: - Data screens	static
NAME	EXTENDED NAME: - Data screens	static
WC05350	FISCAL YEAR END: - Currency conversion	y
BBCHF12	IBA CHF IBK. LIBOR 12M DELAYED - OFFERED RATE: - Calculate DDs	d
BBCHF1M	IBA CHF IBK. LIBOR 1M DELAYED - OFFERED RATE: - Calculate excess returns	d
BBGBP12	IBA GBP IBK. LIBOR 12M DELAYED - OFFERED RATE: - Calculate DDs	d
BBGBP1M	IBA GBP IBK. LIBOR 1M DELAYED - OFFERED RATE: - Calculate excess returns	d
WC07015	INACTIVE DATE: - Data cleaning	static
ISINID	ISIN CODE - PRIMARY/SECONDARY FLAG: - Data screens	static
GGISN	ISIN ISSUER COUNTRY: - Data screens - Creation of dummy variables	static
MAJOR	MAJOR FLAG: - data screens	static
MV	MARKET VALUE: - Calculate DDs - Value-weighted portfolios - Size sorts	d
WC03069	OTHER ACCRUED EXPENSES: - Calculate cash-based gross profitability	y
ASVIB1Y, BIBOR1Y, EOIBK1Y, FNIBF1Y, BBFRF12, BBDEM12, GREURB1Y, EIRED1Y, BBITL12, LNIBK1Y, AIBOR1Y, BBPTE12, SXIBK1Y, BBESP12	OTHER COUNTRY SPECIFIC 1-YEAR RATES: - Calculate DDs	d
WC02140	PREPAID EXPENSES: - Calculate cash-based gross profitability	y
WC02051	RECEIVABLES(NET): - Calculate cash-based gross profitability	y

Table A3. Datastream and Worldscope Items used (continued).

# Mnemonic	Usage	Periodicity
WC03051	SHORT-TERM DEBT & CURRENT PORTION OF LONG-TERM DEBT: - Calculate DDs	y
WC07021	SIC1: Identify banks for calculation of BANK - Exclude financials from the analysis	static
TYPE	STOCK TYPE: - Data screens	static
SWECBSP(ER)	SWISS FRANC TO EURO (ECB) – EXCHANGE RATE: - Currency conversion	d
WC02999	TOTAL ASSETS: - Calculate cash-based gross profitability - Calculate Investment factor	y
WC02101	TOTAL INVENTORIES: - Calculate cash-based gross profitability	y
RI	TOTAL RETURN INDEX: - Calculate daily and monthly stock returns	d
UKECBSP(ER)	UK £TO EURO (ECB) – EXCHANGE RATE: - Currency conversion	d
UP	UNADJUSTED PRICE: - Data screens	d

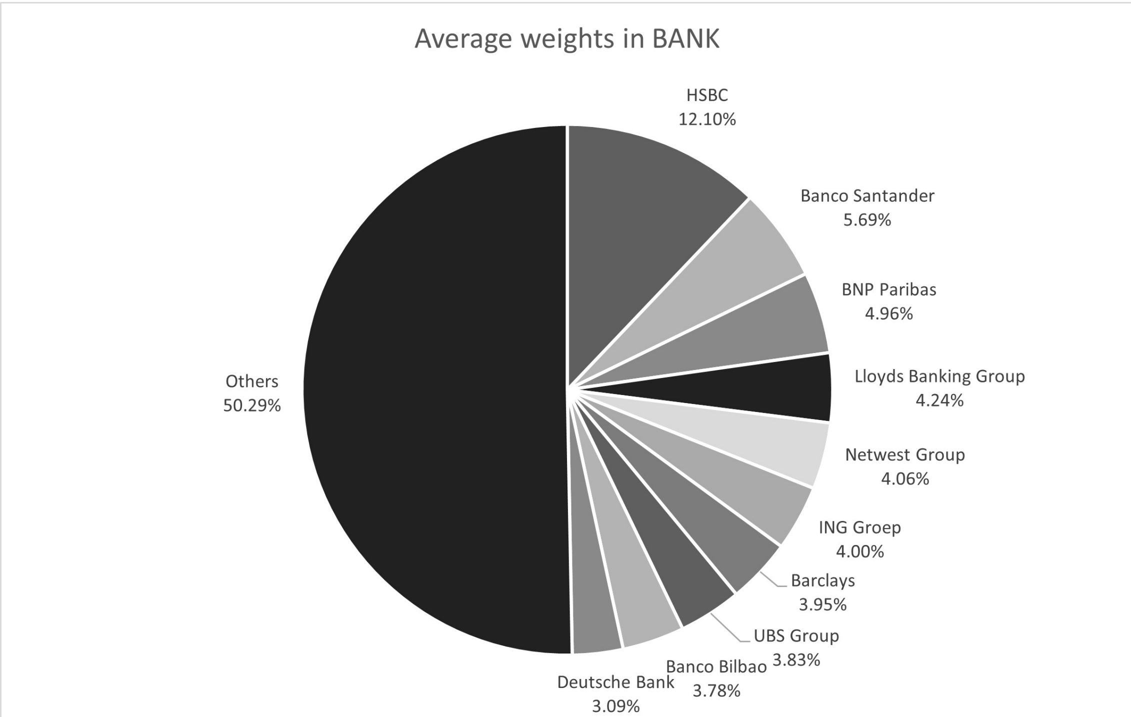

Figure A2. Average weights of banking institutions in BANK from June 1999 to June 2020.

Appendix B. Applied data screens

Table B1. Static screens. This table shows the applied filters based on equities' static data, as obtained via Datastream.

#	Items involved	Description	Reference
1	MV, RI	We require the availability of timeseries of RI and MV.	
2	Major = Y	We require the Major Flag being 'Y,' excluding therefore all securities not listed as major shares.	e.g., Schmidt et al. (2011), Hanauer and Huber (2018)
3	Stock Type = EQ	We require the Stock Type flag being 'EQ,' excluding all non-equities.	e.g., Ince and Porter (2006)
4	ISINID = P	We require the ISINID flag being 'P,' only considering primary listings.	e.g., Hanauer and Huber (2018)
5	Extended Name, ENAME, ECNAME	We filter for 'illegal symbols' in the names specifications of the stocks to exclude duplicates, warrants, ETFs, unit trusts, etc. A complete list of 'illegal symbols' can be found in Table B3.	e.g., Ince and Porter (2006), Griffin, Kelly, and Nardari (2010), Annaert, Ceuster, and Verstegen (2013)
6	GEOGN, GEOLN, ISINCC	Stocks with a county indication different from the country to be analyzed are removed.	e.g., Ince and Porter (2006), Griffin, Kelly, and Nardari (2010), Annaert, Ceuster, and Verstegen (2013)
7	PCUR	Stocks with a currency indication different from the countries to be analyzed currency are removed.	e.g., Griffin, Kelly, and Nardari (2010), Hanauer and Huber (2018)
8	Bourse Name	Stocks with an indicated exchange name different from the countries national stock exchanges are excluded.	e.g., Schmidt et al. (2011)
9	DS-Identifier	The UBS AG (DS-ID: 936458) is removed from the sample, since it is a duplicate of the UBS Group AG (DS-ID: 9215N3) and is not covered by the other described data filters.	

Table B2. Dynamic screens. This table shows the applied filters based on individual stocks to eliminate abnormal data structures, which could potentially influence our analysis, as provided by Datastream and Worldscope.

#	Items	Description	Reference
1	MV, UP, WC03501, WC03263, RI, WC07015	We set all occurring market values, unadjusted prices, book values, and calculated returns to NA after a company's inactive date.	Ince and Porter (2006), Hanauer and Huber (2018)
2	RI	We delete reoccurring returns, preventing illiquid stocks from distorting our results. For three or more reoccurrences in our monthly return data, we set all involved returns to NA. Equivalently, for 90 or more occurrences in our daily data, we set all involved returns to NA.	
3	UP, returns	We set returns to NA in case an unadjusted price greater than 1.000.000 in local currency (either EUR, GBP, or SFR) is observed.	e.g., Schmidt et al. (2011), Hanauer and Huber (2018)
4	UP	We exclude so-called penny stocks in our analyses. We define penny stocks as stocks with an unadjusted price below 1€. When creating our TSF, the unadjusted price at the end of June was considered. In our monthly CSRs, we check for UP_t.	Ince and Porter (2006)
5	Returns	We returns to NA when $R_t > 990\%$.	e.g., Schmidt et al. (2019)
6	Returns	We follow Ince and Porter (2006) and set abnormal returns to NA when R_t or $T_{t-1} > 300\%$ and $(1 + R_t)(1 + R_{t-1}) < 50\%$.	e.g., Ince and Porter (2006)
7	MV	Market Values ≤ 0 are set to NA. However, the corresponding return data are preserved. In this way, the stocks are still subject to our CSR, but are not considered for the construction of factor-mimicking portfolios, which are created as market value-weighted long-short portfolios.	

Table B3. Illegal symbols. This table lists the illegal symbols used to exclude stocks with unwanted properties globally or per country. The list is mainly taken from Hanauer and Huber (2018).

County	Items involved
All	1000DUPL, DULP, DUP, DUPE, DUPL, DUPLI, DUPLICATE, XSQ, XETa, ADR, GDR, PF, PF, PFD, PREF, PREFERRED, PRF, WARR, WARRANT, WARRANTS, WARRT, WT, WTS, WTS2, %, DB, DCB, DEB, DEBENTURE, DEBENTURES, DEBT, .IT, .ITb, INV, INV TST, INVESTMENT TRUST, RLST IT, TRUST, TRUST UNIT, TRUST UNITS, TST, TST UNIT, TST UNITS, UNIT, UNIT TRUST, UNITS, UNT, UNT TST, UT, AMUNDI, ETF, INAV, ISHARES, JUNGE, LYXOR, X-TR,EXPD, EXPIRED, EXPIRY, EXPY, ADS, BOND, CAP.SHS, CONV, CV, CVT, DEFER, DEP, DEPY, ELKS, FD, FUND, GW.FD, HI.YIELD, HIGH INCOME, IDX, INC.&GROWTH, INC.&GW, INDEX, LP, MIPS, MITS, MITT, MPS, NIKKEI, NOTE, OPCVM, ORTF, PARTNER, PERQS, PFC, PFCL, PINES, PRTF, PTNS, PTSHP, QUIBS, QUIDS, RATE, RCPTS, REAL EST, RECEIPTS, REIT, RESPT, RETUR, RIGHTS, RST, RTN.INC, RTS, SBVTG, SCORE, SPDR, STRYPES, TOPRS, UTS, VCT, VTG.SAS, XXXXX, YIELD, YLD
AT	PC, PARTICIPATION CERTIFICATE, GENUSSSCHEINE, GENUSSCHEINE
BE	VVPR, CONVERSION, STRIP
FI	USE
FR	ADP, CI, SICAV, ““)SICAV““), SICAV-
DE	GENUSSCHEINE
GR	PR
IT	RNC, RP, PRIVILEGES
NL	CERTIFICATE, CERTIFICATES, CERTIFICATES““), CERT, CERTS, STK““.
UK	PAID, CONVERSION TO, NON-VOTING, CONVERSION A
CH	CONVERTED INTO, CONVERSION, CONVERSION SEE

Appendix C. Additional Descriptive Statistics

Table C1. EMU+ moments and correlations (winsorized) in % per month; This table shows the descriptive statistics of our bank-specific factors, as well as commonly used risk factors in asset pricing. The factors are winsorized at the 1% and 99% levels. All factors (except for dCDSS) are calculated from the sample data and from June 1999 to June 2020. The descriptive statistics of the dCDSS cover the shorter period from January 2008 to June 2020.

	MKTrf	BANK	BMMkt	dCDSS	SMB	HML	RMW	CMA
Moments								
Mean	0.41	0.01	-0.43	1.64	0.11	0.35	0.37	0.29
Median	0.89	0.02	-0.20	-2.18	0.23	0.36	0.22	0.19
SD	4.01	0.17	3.50	17.30	2.37	2.42	1.55	1.87
Skewness	-0.57	-0.79	-0.05	1.08	-0.49	0.20	0.22	0.76
Kurtosis	3.61	4.68	3.28	4.59	4.01	5.61	3.57	4.50
Cross-Correlations in %								
MKT-rf	100	61.50	23.55	-55.26	3.44	-8.90	-14.87	-39.17
BANK	61.50	100	56.08	-49.06	24.33	9.47	-17.41	-17.70
BMMkt	23.55	56.08	100	-40.09	27.67	39.46	-35.04	11.04
dCDSS	-55.26	-49.06	-40.09	100	-10.13	-36.70	42.30	7.40

Appendix D. Additional Portfolio sorts

Table D1. DE Portfolio returns for sorted portfolios on BMMkt-βs. This table shows the average excess returns of each single or double-sorted portfolio in % per month for the German stock market. The single-sorted portfolios are created using time-varying univariate BMMkt-βs from equation (6), whereas the double-sorted portfolios are based on the bivariate βs from equation (7). Hi-Lo indicates the return difference between the highest-ranked BMMkt-β portfolios and the lowest-ranked BMMkt-β portfolios. The corresponding t-stat is represented as an absolute value (H_0: Hi-Lo equals zero). The portfolios are created from June 1999 to June 2020. Firms with SIC codes between 6000 and 6999 are excluded.

Panel A: Single-sorted portfolios on BMMkt-βs						
Quintiles	BMMkt1	BMMkt2	BMMkt3	BMMkt4	Hi-Lo	|t-stat|
Returns	0.090	0.442	0.596	0.829	0.739	1.515

Panel B: Double-sorted portfolios on MKTrf- and BMMkt-βs						
Quintiles	BMMkt1	BMMkt2	BMMkt3	BMMkt4	Hi-Lo	|t-stat|
MKTrf1	0.396	0.085	0.826	0.412	0.016	0.029
MKTrf2	0.438	1.029	0.724	0.769	0.331	0.762
MKTrf3	0.195	0.814	0.831	0.674	0.478	1.212
MKTrf4	0.268	-0.058	0.431	1.280	1.012	2.207

Appendix E. Additional Fama–MacBeth Regressions

Table E1. EMU+ Fama–MacBeth regression results using BANK-βs. This table shows time series averages in % per month of the cross-sectional OLS estimates as per equations (10) and (11), as well as the EIV-corrected estimates following Chordia, Goyal, and Shanken (2015) as per equations (12) and (16). Firms with SIC codes between 6000 and 6999 are excluded. We control for country effects using dummy variables. We report the absolute t-values (based on Newey—West standard errors) to H_0—the coefficient is indistinguishable from 0—between parentheses. CSRs are performed each month from June 1999 to June 2020.

	OLS1	OLS2	OLS3	EIV1	EIV2	EIV3
Intercept	0.67**	0.60**	0.50	0.69**	0.58**	0.75
	(2.2935)	(2.1184)	(1.3768)	(2.5138)	(2.322)	(1.4119)
BANK-β	0.00	0.00	0.00	0.02	0.01	0.03
	(0.4932)	(1.0707)	(0.8372)	(1.0146)	(1.0301)	(1.6091)
MKTrf-β	-0.11	-0.03	-0.06	-0.13	-0.09	-0.50
	(0.7287)	(0.2761)	(0.4213)	(0.4236)	(0.3798)	(1.4187)
SMB-β		0.06	0.02		0.13	0.14
		(1.2632)	(0.4896)		(1.2433)	(0.6432)
HML-β		0.13	0.13		0.15	0.20
		(1.3362)	(1.4368)		(0.9261)	(1.1734)
CMA-β		0.03	0.06		0.02	0.21
		(0.4561)	(0.84)		(0.165)	(1.2997)
RMW-β		-0.03	0.00		0.00	0.20
		(0.9095)	(0.0458)		(0.0126)	(1.3859)
ln(Size)			-0.01			-0.01
			(0.1561)			(0.1415)
ln(BM)			0.11			-0.27
			(1.2212)			(0.6896)
CbGP			0.70***			0.25
			(6.1808)			(0.9384)
Inv			-0.01			-0.13**
			(0.8971)			(2.0165)
R^2	0.0412	0.0496	0.0615			
Adj. R^2	0.0341	0.0413	0.0513			
Avg. n	3014.5929	3014.5929	2599.6957	3014.5929	3014.5929	2054.6759

Table E2. DE Fama–MacBeth regression results using BMMkt-βs. This table shows time series averages in % per month of the cross-sectional OLS estimates as per equations (10) and (11), as well as EIV-corrected estimates following Chordia, Goyal, and Shanken (2015) as per equations (12) and (16). Firms with SIC codes between 6000 and 6999 are excluded. We report the absolute t-values (based on Newey–West standard errors) to H_0—the coefficient is indistinguishable from 0—between parentheses. CSRs are performed each month from June 1999 to June 2020.

	OLS1	OLS2	OLS3	EIV1	EIV2	EIV3
Intercept	0.54**	0.53**	-0.02	0.68***	0.58***	-0.30
	(2.1465)	(2.2962)	(0.0603)	(3.0722)	(2.7122)	(0.8616)
BMMkt-β	0.49**	0.49**	0.27*	0.56	0.41	-0.33
	(2.3926)	(2.2353)	(1.7617)	(1.5044)	(0.9953)	(0.951)
MKTrf-β	-0.28	-0.23	-0.25	-0.54	-0.33	-0.66**
	(1.2213)	(1.1244)	(1.1252)	(1.5875)	(0.8697)	(1.9714)
SMB-β		0.18	0.11		0.29	0.37
		(1.6228)	(1.067)		(0.8375)	(1.4831)
HML-β		0.14	0.14		0.33	0.04
		(0.8286)	(0.8794)		(1.0805)	(0.1259)
CMA-β		0.07	0.07		-0.07	0.41
		(0.5115)	(0.5222)		(0.1612)	(1.5574)
RMW-β		0.07	-0.01		0.27	0.29
		(0.8968)	(0.0725)		(1.0555)	(1.3169)
ln(Size)			0.07**			0.18***
			(2.399)			(3.0621)
ln(BM)			0.02			-0.07
			(0.3248)			(0.5177)
CbGP			0.93***			0.66***
			(6.1178)			(3.0574)
Inv			-0.18*			-0.11
			(1.8762)			(0.5073)
R^2	0.0301	0.0568	0.0837			
Adj. R^2	0.0261	0.0451	0.0611			
Avg. n	497.8142	497.8142	421.3083	497.8142	497.8142	344.0553