Discussion paper

BACK TO THE BASICS IN BANKING? A MICRO-ANALYSIS OF BANKING SYSTEM STABILITY

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Back to the Basics in Banking? A Micro-Analysis of Banking System Stability.*

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Abstract

This paper analyzes the relationship between banks' divergent strategies toward specialization and diversification of financial activities and their ability to withstand a banking sector crash. We first generate market-based measures of banks' systemic risk exposures using extreme value analysis. Systemic banking risk is measured as the tail beta, which equals the probability of a sharp decline in a bank's stock price conditional on a crash in a banking index. Subsequently, the impact of (the correlation between) interest income and the components of non-interest income on this risk measure is assessed. The heterogeneity in extreme bank risk is attributed to differences in the scope of non-traditional banking activities: non-interest generating activities increase banks' tail beta. In addition, smaller banks and better-capitalized banks are better able to withstand extremely adverse conditions. These relationships are stronger during turbulent times compared to normal economic conditions. Overall, diversifying financial activities under one umbrella institution does not

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improve banking system stability, which may explain why financial conglomerates trade at a discount.

Keywords: diversification, non-interest income, financial conglomerates, banking stability, extreme value analysis, tail risk.

JEL: G12, G21, G28.

1 Introduction

The subprime crisis reminds us that, notwithstanding a period of disintermediation, the banking sector remains a particularly important sector for the stability of the financial system. Moreover, disruptions in the smooth functioning of the banking industry tend to exacerbate overall fluctuations in output. Consequently, banking crises are associated with significant output losses. It follows that preserving banking sector stability is of the utmost importance to banking supervisors. That is, regulators are especially interested in the frequency and magnitude of extreme shocks to the system which threaten the smooth functioning (and ultimately the continuity) of the banking system. Banking sector supervisors and central banks' main interest is to maintain and protect the value of their portfolio of banks in times of market stress. Thus it is interesting to study the factors contributing to the riskiness of the portfolio.

In this spirit, an extensive literature[1] reviews banking crises around the world, examining the developments leading up to the crises as well as policy responses. Initial research focussed on macro-prudential supervision and investigates the relationships between macro-economic conditions and banking system stability (see e.g. Demirgüc-Kunt and Detragiache, 1998; Eichengreen and Rose, 1998). Subsequently, attention shifted towards the impact of the regulatory and institutional environment on banking crises (see e.g. Barth, Caprio and Levine, 2004; Beck, Demirgüc-Kunt and Levine, 2006; Demirgüc-Kunt and Detragiache, 2002; Houston, Lin, Lin and Ma, 2008). However, not all banks need to contribute equally to the risk profile of the supervisor's portfolio and the stability of the banking system. Nevertheless, research that zooms in at the micro-level and aims to identify bank-specific characteristics of banking system stability is limited. Moreover, almost all evidence is based on analyzing the determinants of outright bank failures in the US (see e.g. Gonzalez-Hermosillo, 1999, and the references in Appendix 1 of that paper; and Wheelock and Wilson, 2000).

This paper investigates why some banks are better able to shelter themselves from the storm by analyzing the bank-specific determinants of individual banks' contribution to systemic banking risk. Our research contributes to the banking literature in a number of ways. First, a crucial addition to the analysis is our measure of individual bank risk during extremely adverse economic conditions. More precisely, we estimate tail betas (Hartmann, Straetmans and de Vries, 2006 and Straetmans, Verschoor and Wolff, 2008) rather than analyzing actual defaults. Tail beta measures the probability of a crash in a bank's stock conditional on a crash in a Euro-

[1] Cihak and Schaeck (2007) provide an excellent overview of the empirical literature on the determinants of banking system stability.

pean banking sector stock price index. The choice of this measure is driven by two empirical stylized facts on banking panics. Historically, banking panics occurred when depositors initiated a bank run. In more recent periods, banks face a stronger disciplining role by stock market participants. As a consequence, equity and bond market signals are good leading indicators of bank fragility (Gropp, Vesala and Vulpes, 2006). Therefore, we employ a market-based measure. In addition, Gorton (1988) and Kaminsky and Reinhart (1999) document that most banking panics have been related to systemic and macroeconomic fluctuations rather than 'mass hysteria' or self-fulfilling prophecies. Therefore, we look at the conditional rather than the unconditional probability of a crash in a bank's stock price. By measuring the tail beta for all listed European banks over different time periods we document the presence of substantial cross-sectional heterogeneity and time variation in the tail betas of European banks.

Second, we contribute to the debate on the scope of financial firms by analyzing the impact of revenue diversity on banking system stability. In recent years, one of the major developments in the banking industry has been the dismantling of the legal barriers to the integration of distinct financial services and the subsequent emergence of financial conglomerates. In Europe, the Second banking Directive of 1989 allowed banks to combine banking, insurance and other financial services under a single corporate umbrella. Similar deregulating initiatives took place in the US by means of the Gramm-Leach-Bliley Act of 1999. These deregulations resulted in an expansion in the variety of activities and financial transactions in which banks engaged. Most of the existing research addressing the issue of the economies of scope in financial corporations takes an industrial organization approach and analyzes whether financial conglomerates create or destroy value (see e.g. Laeven and Levine, 2007; Schmid and Walter, 2009). Recent studies also analyze whether functional diversification reduces bank risk by investigating functional diversification from a portfolio perspective (see e.g. Baele, De Jonghe and Vander Vennet, 2007; Stiroh, 2006). We contribute to the empirical literature on revenue diversity of financial corporations by addressing a third perspective, that of financial stability. Our results establish that the shift to non-traditional banking activities, which generate commission, trading and other non-interest income, increases banks' tail betas and thus reduces banking system stability. Interest income is less risky than all other revenue streams. Other indicators of bank specialization in traditional intermediation, such as a higher interest margin or higher loans-to-asset ratio, corroborate the finding that traditional banking activities result in lower systemic banking risk. This questions the usefulness of financial conglomeration as a risk diversification device, at least in times of stock market turmoil. The results are consistent with the theoretical predictions of Wagner (2008) that even though diversification may reduce each bank's probability of default, it makes systemic crises more likely. However, we also document that the extent to which shocks to the various income shares are correlated matters for overall and extreme bank risk.

Third, we attribute a substantial degree of the time and cross-sectional heterogeneity to other bank-specific characteristics. The variables we include capture the constituents of the CAMEL rating methodology, i.e. Capital adequacy, Asset quality, Management quality, Earnings, Liquidity. Appendix 1 of Gonzalez-Hermosillo (1999) provides an interesting overview of the variables used in selected empirical studies on US bank failures and also classifies these according to the constituents of the CAMEL rating. Wheelock and Wilson (2000) use similar variables to analyze why banks disappear. Smaller banks and well-capitalized banks contribute significantly to a safer banking system. In terms of economic impact, the latter results are somewhat larger than the gains from focussing on the traditional intermediation activities.

Finally, we show that the focus on extreme bank risk and banking system stability provides insights supplementary to the existing evidence on banks' riskiness in normal economic conditions. The information content of tail betas differs from measures focussing on central dependence or composite risk measures (such as long-term debt ratings or equity return volatility). We obtain, for instance, that higher capital buffers work best when they are needed the most, i.e. in times of stress.

The following section reviews relevant literature on banking system stability, the risk-taking incentives of financial conglomerates and the impact of revenue diversity on bank risk. In Section 3, we discuss the sample composition. The next section describes the methodology to measure banks' tail betas. The subsequent section, Section 5, is divided into three subsections. The first subsection introduces the results for the drivers of heterogeneity in systemic banking risk. In a panel set-up, we relate the tail betas to different types of financial revenues and other bank-specific variables. While these issues are always important, the magnitude of the recent financial crisis renews interest in these questions. The second subsection documents that the information content of the tail beta differs significantly from the information contained in central dependence measures (such as the traditional OLS beta between bank stock returns and returns on a banking index). Subsection 5.3. deals with refinements on the panel data set-up and robustness of the baseline regression. We show that the results are not driven by reverse causality or particular events (such as M&As, IPOs, delisting or banking crises) that may create a sample selection bias. Furthermore, we scrutinize the impact of composite risk measures (such as ratings or volatility) on the tail beta as well as control for the stability of the results in subsamples based on bank size. Section 6 concludes with policy implications.

2 Literature review

2.1 Banking regulation and systemic banking risk: selected literature

Systemic banking risk can be defined as an event that affects a considerable number of financial institutions in a strong sense, thereby severely impairing the general well-functioning of the financial system. This well-functioning of the financial system relates to the effectiveness and efficiency with which savings are channelled into the real investments promising the highest returns (de Bandt and Hartmann, 2002). Hence, historically, most of the banking regulation that was put in place was designed to reduce systemic risk.

In many countries, one of the most important measures to reduce systemic risk is currently capital regulation in the form of the Basel agreements. In all standard models of banking, high capital levels are associated with a lower bankruptcy risk (Santos, 2001). However, current regulation is based only on a bank's own risk and ignores the externalities of the bank's actions. Acharya (2009) shows that such regulation may leave the collective risk-shifting incentive unattended, and can, in fact, accentuate systemic risk. He concludes that prudential supervision should thus operate at a collective level, and regulate each bank such that the capital adequacy requirement is increasing in the individual risk of each bank as well as in the correlation of banks' risks.

Next to capital regulation, deposit insurance schemes are put in place to prevent bank runs by depositors. Explicit deposit insurance has become increasingly popular, and a growing number of depositors around the world are now sheltered from the risk of bank failure. However, according to the findings of Demirgüc-Kunt and Detragiache (2002), explicit deposit insurance may also be detrimental to bank stability, the more so where bank interest rates have been deregulated and where the institutional environment is weak. Hence, where institutions are good, opportunities for moral hazard are more limited, and more effective regulation and prudential supervision better offset the adverse incentives created by deposit insurance.

Regulation often tends to increase after a severe and systemic crisis. In the aftermath of the stock market crash of 1929 and the Great Depression, the Banking Act of 1933, better known as the Glass-Steagall Act, separated the activities of commercial banks and investment banks. The idea behind it was twofold: first, diffuse excessive concentration of financial power in a limited number of large institutions, and second, prevent unsophisticated investors from being sold risky investments. However, over time there has been some deregulation. The Glass-Steagall Act was abolished by a series of laws from the 1980s (relaxation of branching restrictions) until the late 1990s (culminating in the Gramm-Leach-Bliley in 1999). The main effect of this deregulation was permitting American banks to do what European banks had long been allowed to do, the combination of various types of financial activities under one umbrella institution (since the Second Banking Directive of 1989). However, there is little theoretical or empirical guidance as to whether revenue diversity helps or harms banking system stability.

2.2 Revenue diversity and bank risk: selected literature

Most of the theoretical and empirical literature that studies the effects of combining different activities under one umbrella institution focus on the performance component. This focus on the benefit or discount that conglomeration creates can be justified for non-financial corporations; however, the risk aspect is at least as important, if not more so, for financial corporations. Unfortunately, little theoretical guidance exists on the impact of diversified revenue streams on the risk-taking behavior of financial institutions. The main sources of the potential risk-reducing effects of revenue diversity are the less than perfect correlations between different activities (Dewatripont and Mitchell, 2005) and the organizational structure of the conglomerate (Freixas, Loranth and Morrison, 2007). Wagner (2008) documents that diversification at financial institutions entails a trade-off. Functional diversification may reduce idiosyncratic risk, but it also makes systemic crises more likely.

A number of authors empirically identify the impact of combining different financial activities on a bank's risk profile during normal economic conditions. Evidence for the US[2] documents that in the 1990s securities and insurance activities both had the potential to decrease conglomerate risk, but the effect largely depends on the type of diversifying activities that bank holding companies undertake. Expanding banks' activities may

[2]Despite the fact that the scope for functional diversification has been deregulated earlier and more completely in Europe, most of the empirical evidence is based on US data.

reduce risk, with the main risk-reduction gains arising from insurance rather than securities activities (see e.g. Kwan and Laderman, 1999 and Saunders and Walter, 1994). Moreover, diversification of non-traditional banking activities leads to a lower cost of debt (Deng, Elyasani and Mao, 2007). However, these arguments are contradicted somewhat by more recent findings (DeYoung and Roland, 2001; Stiroh, 2004a; Stiroh, 2004b and Stiroh and Rumble, 2006). For the US, studies using accounting data suggest that an increased reliance on non-interest income raises the volatility of accounting profits without significantly raising average profits. There are only small diversification benefits for Bank Holding Companies and the gains are offset by the increased exposure to more volatile non-interest income activities for more diversified US banks. Results based on US equity data (Stiroh, 2006) arrive at a similar conclusion. For a sample of US banks over the period 1997-2004, no significant link between non-interest income exposure and average returns across banks can be established. On the other hand, the volatility of market returns is significantly and positively affected by the reliance on non-interest income.

European banks that have moved into non-interest income activities present a higher level of risk than banks which mainly perform traditional intermediation activities (Mercieca, Schaeck and Wolfe, 2007). Moreover, risk is mainly positively correlated with the share of fee-based activities but not with trading activities (Lepetit, Nys, Rous and Tarazi, 2008). Recent research linking the effect of diversification to market-based measures of performance and riskiness (and the risk/return trade-off) finds that banks with a higher share of non-interest income in total income are perceived to perform better in the long run (Baele et al., 2007). However, this better performance is offset by higher systematic risk. Diversification of revenue streams from different financial activities increases the systematic risk of banks i.e., the stock prices of diversified banks are more sensitive to normal fluctuations in a general stock market index than non-diversified banks. Finally, using a worldwide sample, de Nicolo, Barthlomew, Zaman and Zephirin (2004) report that conglomerates exhibit a higher level of risk-taking than non-conglomerates.

All of this evidence addresses normal economic conditions, however, regulators are especially interested in the frequency and magnitude of extreme events. To the best of our knowledge, only Schoenmaker, Slijkerman and de Vries (2005) take this perspective and analyze the dependence between the downside risk of European banks and insurers. However, their analysis is limited to ten banks and ten insurers. Schoenmaker et al. (2005) investigate whether the extreme risk profile of artificially mixed pairs differs from the risk profile of bank-bank combinations. They argue that if the risk profile of both sectors is different, this should create risk diversification possibilities for financial conglomerates and increase financial sector stability.

Most of the available evidence identifies relationships between functional diversification and bank risk in normal economic conditions. However, it is not clear how diversified financial institutions will behave in adverse economic situations and what the overall impact of revenue diversification on banking sector stability will be under these circumstances. This paper attempts to fill this void.

3 The sample

Since the purpose of the analysis is to investigate how diversity in bank revenue affects European banks' extreme systemic and systematic risk, we employ both accounting data and stock price information. We extract information from two data sources. For balance sheet and income statement data, we rely on the Bankscope database, which provides comparable information across countries. Bankscope does not provide stock price information on a daily basis; hence we use Datastream to obtain information on daily stock returns and market capitalization. We match both datasets on the basis of the ISIN-identifier (an identification system similar to the CUSIP number in the US and Canada) for the listed banks. Unfortunately, Bankscope does not provide the ISIN-number for delisted banks. For the delisted banks, we match the information from the two datasets using information on some basic accounting data (e.g. total assets, equity,... which are also provided by Datastream). In a similar fashion, we verify the matching of the listed banks.

We carry out the analysis for the banks that have their headquarters in one of the countries of the European Union (before enlargement, i.e. with 15 member states). Our sample consists of both commercial banks and bank holding companies. The sample period is to a large extent fixed by the availability of comparable data over time. While Bankscope contains information from 1987 onwards, the coverage is only substantial from the early nineties. Therefore, we perform the analysis on the sample period 1992-2007. The time span of the sample ensures that it contains periods with different business cycle conditions and stock market conditions.

We perform a number of selection criteria. First, we only include banks for which we can obtain at least six consecutive years of accounting and stock market information. This restriction is imposed because we use extreme value analysis to model extreme bank risk. In extreme value analysis, large samples are needed since only a fraction of the information is used in the estimations. Six consecutive years of daily stock prices yield at least 1500 observations, a sample size that is feasible to apply extreme value analysis, though close to the lower bound[3] of the existing applications in finance. Second, following common practice in the finance literature, we impose a liquidity criterion on the stock returns. The rationale is that infrequently traded stocks may not absorb information accurately. We measure liquidity by the number of daily returns that are zero. However, in this analysis we can be rather mild on the imposed liquidity criterion. We only disregard stock if more than 60% of the daily returns are zero returns. Hence, we assume that although these bank stocks are very illiquid, their non-zero returns most likely reflect important, extreme events that are informative for our purposes. Moreover, their zero returns will not affect our estimates of extreme risk, since the tail of the distribution will still contain the extreme movements in banks' stock prices.

Due to delistings, IPOs, and mergers and acquisitions, our dataset is unbalanced. Some banks are only listed for six years whereas others have been operational and listed for a longer period. Comparing banks' behavior and risk profile is only sensible if each bank's characteristics are measured over the same time interval. One possibility is to consider only those banks that are active (and listed) over the entire period. However, in this case, useful information on the other banks is neglected and may induce a selection bias. We opt for a different approach. We measure banks' extreme systemic risk exposures over moving windows of six years. The first period covers the years 1992-1997. In each subsequent subsample, we drop the observations of the initial sample year and add a more recent year of data. Since the sample period spans 16 years, we obtain 11 rolling subsamples of six years. Hence, at each point in time, we can meaningfully compare the cross-sectional differences in banks' risk profile. In general, the composition of the bank set will be different in each subperiod.

4 A stock market-based measure of bank stability

As the stock market moves, each individual asset is more or less affected. The extent to which any asset participates in such general market moves determines that asset's systematic risk. In general, systematic risk is measured using a firm's beta and is computed by dividing the covariance between the firm's stock returns and the market return by the variance of the market returns. However, firms' exposure to systematic risk need not be constant over time. In particular, systematic risk exposures may vary over the business cycle or can be different in normal times versus times of market turbulence. While the combination of correlation-based methods and

[3]We also perform the analysis on moving subsample of 8 years. The results are very similar.

assuming multivariate normality may yield acceptable results for central dependence measures, there exists abundant evidence that marginal and joint distributions of stock returns are not normally distributed, especially in the tail area. This might be solved by modelling the tail behavior with fat-tailed distributions. However, this requires distributional assumptions or knowledge of the underlying return processes. Choosing the wrong probability distribution may be problematic since correlations are non-robust to changing the underlying distributional assumptions of the return processes (Embrechts, Klüppelberg, Mikosch, 1999). Moreover, many of the multivariate distributions lead to models that are non-nested, which cannot be tested against each other. Extreme value analysis overcomes these problems. It enables estimation of marginal and joint tail behavior without imposing a particular distribution on the underlying returns.

In mathematical terms, we are interested in the following expression: $P(X > x \mid Y > y)$. This expression captures the conditional probability that the return on one asset, X, exceeds a certain threshold x conditional on observing that the return on another asset, Y, exceeds y. This conditional probability reflects the dependence between two return series X and Y. We adopt the convention to take the negative of the return when outlining the methodology. x and y are thresholds in the tail of the distributions, such that they correspond with situations of large losses. In general, x and y may differ across stocks (especially in our analysis where Y is the return on a portfolio and X is single stock), but we impose that they correspond to outcomes that are equally (un)likely to occur. That is, the unconditional probability that an asset crashes equals $p = P(X > x) = P(X > Q_x(p)) = P(Y > Q_y(p))$, where Q_x and Q_y are quantiles.

The conditional co-crash probability can be rewritten as:

$$P(X > Q_x(p) \mid Y > Q_y(p)) = \frac{P(X > Q_x(p), Y > Q_y(p))}{P(Y > Q_y(p))} \tag{1}$$

In general, X and Y can be the returns generated by any kind of asset. However, if the conditioning asset Y is a broad market or (banking) sector portfolio, the conditional probability can be seen as a tail extension of a regression based β obtained in classical asset pricing models. The resulting co-crash probabilities provide an indication of extreme systematic or systemic bank risk. Hence, an asset's co-crash probability with the banking sector (or market), $P(X > Q_x(p) \mid Y > Q_y(p))$, will be labelled tail-$\beta$ (Straetmans et al., 2008).

To obtain the tail-β, we only need an estimate of the joint probability in the numerator. The denominator is determined by p. We implement the approach proposed by Ledford and Tawn (1996) and closely follow

Hartmann et al. (2006). This approach is semi-parametric and allows both for asymptotic dependence and asymptotic independence[4]. Hence, we can avoid making (wrong) distributional assumptions on the asset returns. This approach has recently been used in the finance literature by Hartmann et al. (2006), Poon, Rockinger and Tawn (2004) and Straetmans et al. (2008).

The joint probability is determined by the dependence between the two assets and their marginal distributions. In order to extract information on the (tail) dependence, we want to eliminate the impact of the different marginal distributions. Therefore, we transform the original return series X and Y to series with a common marginal distribution. If one transforms the different return series to series with a common marginal distribution, the impact of marginals on the joint tail probabilities is eliminated. This means that differences in the conditional crash probabilities of banks are purely due to differences in the tail dependency of extreme returns. The theoretical (a) and empirical (b) counterpart of transforming the stock returns to unit Pareto marginals[5] are based on the following equations:

$$(a)\ \widetilde{X}_i = \tfrac{1}{1-F(X_i)} \quad and \quad (b)\ \widetilde{X}_i = \tfrac{n+1}{n+1-R_{X_i}} \tag{2}$$

where $i = 1, ..., n$ and R_{X_i} is the rank order statistic of return X_i. Since $\widetilde{X}_i$ and $\widetilde{Y}_i$ have the same marginal distribution, it follows that the quantiles $Q_{\widetilde{x}}(p)$ and $Q_{\widetilde{y}}(p)$ now equal $q = 1/p$.

The transformation of the return series affects the numerator of the co-crash probability as follows:

$$P(X > Q_x(p), Y > Q_y(p)) = P(\widetilde{X} > q, \widetilde{Y} > q) = P(\min(\widetilde{X}, \widetilde{Y}) > q) \tag{3}$$

Hence, the transformation to unit Pareto marginals reduces the estimation of the multivariate probability to a univariate set-up. The univariate exceedance probability of the minimum series of the two stock returns, $Z = \min(\widetilde{X}, \widetilde{Y})$, can now be estimated using techniques that are standard in univariate extreme value analysis[6]. The only assumption that has to be made is that the minimum series $Z = \min(\widetilde{X}, \widetilde{Y})$ also exhibits fat tails.

[4]Asymptotic dependence means that the conditional tail probability defined on (X, Y) does not vanish in the bivariate tail. With asymptotic independence, the co-exceedance probability decreases as we move further into the bivariate tail.

[5]Other transformations are also feasible. Poon et al. (2004) transform the return series to unit Fréchet marginals. However, the estimates have a larger bias for Fréchet distributions (Draisma, Drees, Ferreira and De Haan, 2004).

[6]In the remainder of this section, we still use Z to refer to the return series. In our specific case, Z is the series created by taking the minimum of $\widetilde{X}$ and $\widetilde{Y}$. Note, however, that Z may also be the return series of a single (untransformed) stock if one wants to model unconditional tail risk.

Univariate tail probabilities for fat-tailed random variables can be estimated by the semi-parametric probability estimator from De Haan, Jansen, Koedijk and de Vries. (1994):

$$\widehat{p}_q = P(Z > q) = \frac{m}{n}\left(\frac{Z_{n-m,n}}{q}\right)^{\widehat{\alpha}} \tag{4}$$

$Z_{n-m,n}$ is the "tail cut-off point", which equals the $(n-m)^{th}$ ascending order statistic, in a sample of size n, of the newly created minimum series Z. The advantage of this estimator is that one can extend the crash levels outside the domain of the observed, realized returns. Note that the tail probability estimator is conditional upon the tail index α and a choice of the number of tail observations used, m. This tail index captures the decay in the probability with which ever more extreme events occur (jointly). A relatively high tail index corresponds with a relatively low probability of extreme events. The tail index α is traditionally estimated using the Hill estimator (1975):

$$\widehat{\alpha}(m) = \left[\frac{1}{m}\sum_{j=0}^{m-1}\ln\left(\frac{Z_{n-j,n}}{Z_{n-m,n}}\right)\right]^{-1} \tag{5}$$

In this equation, $Z_{n-j,n}$ denotes the $(n-j)$-th ascending order statistic from the return series $Z_1, ..., Z_n$. The parameter m is a threshold that determines the sample fraction on which the estimation is based (i.e. the number of extreme order statistics that are used). This parameter is crucial. If one sets m too low, too few observations enter and determine the estimation. If one considers a large m, non-tail events may enter the estimation. Hence, if one includes too many observations, the variance of the estimate is reduced at the expense of a bias in the tail estimate. This results from including too many observations from the central range. With too few observations, the bias declines but the variance of the estimate becomes too large. Asymptotically, there exists an optimal m at which this bias-variance trade-off is minimized.

A number of methods have been proposed to select m in finite samples. First, a widely used heuristic procedure in small samples is to plot the tail estimator as a function of m and select m in a region where $\widehat{\alpha}$ is stable. This procedure is usually referred to as the Hill plot method. Besides being arbitrary, this is difficult to implement if one considers many stock returns. A second option is to determine the optimal sample fraction, m, using a double bootstrap procedure (Danielsson, Haan, Peng and de Vries, 2001). However, this procedure requires, in general, samples that are longer than the one we observe (and it requires heavy computing power).

We apply a third method which directly estimates a modified Hill estimator that corrects for the bias/variance trade-off (Huisman, Koedijk, Kool and Palm, 2001). Huisman et al. (2001) note that the bias is a linear function of m and that the variance is inversely related to m. The modified estimator extracts information from a range of conventional Hill estimates that differ in the number of tail observations included. Weighted least squares is then used to fit a linear relationship between $\widehat{\alpha}(m)$ and m, with the weights proportional to m. The intercept of that regression yields an unbiased estimate of the tail index. Note that, by using a large number of values of m, this bias-corrected method is designed to reduce sensitivity to the single choice of m required by the Hill procedure. A drawback of this method is that it only provides an unbiased measure of the tail index without specifying the optimal sample fraction m. However, this info is still needed to compute the univariate crash probabilities $\widehat{p}_q$. Therefore, after estimating the optimal $\widehat{\alpha}$, we perform an automated grid search to find a stable region in the Hill plot that is as close as possible to the optimal tail index. m is then taken as the midpoint from this region.

Combining equations (1), (4), and (5) allows computing the extreme systematic risk measure, tail-β:

$$TAIL_{\beta} = \frac{\frac{m}{n}\left(Z_{n-m,n}\right)^{\alpha}}{p^{1-\alpha}} \tag{6}$$

We will estimate this tail-β for listed European banks observed over multiple time periods to get an indication of the time evolution and the cross-sectional dispersion in banks' extreme risk sensitivities. The estimated tail betas provide insights in the dependence of events that happen with a certain probability p. In this section and in the remainder of the paper, we model extreme events that happen with a probability of 0.04%. Given that we are using daily data, a probability of 0.04% corresponds to a situation that occurs on average once every 10 years ($= (250 \cdot p)^{-1}$). The probability of the event obviously affects the severity. More likely events are associated with less severe crashes. How does the level of p affect the tail-β? This depends on the estimated tail dependence coefficient (the tail index α of the joint tail). Asymptotic dependence ($\alpha = 1$) implies that the conditional tail probability converges to a non-zero constant. However, asymptotic independence ($\alpha > 1$) results in vanishing co-crash probabilities in the joint tail. In our sample, both asymptotic dependence and independence are present. Hence, for the latter, the tail-β will be larger for less extreme events. For example, setting the crash probability at p=0.001, a level corresponding to the Basel II guidelines, results in less severe events but higher tail betas. In the remainder of the paper, we relate tail betas to bank-specific characteristics. We fix p at 0.04%. Nevertheless, we also experimented with probabilities in the range of $[0.004\%, 0.4\%]$, resulting in events that happen as infrequently as once every 100 years to yearly events. All reported results with respect to the determinants of tail risk are similar (and are available upon request).

Measuring systemic banking risk: results

We are interested in assessing the extent to which individual banks are exposed to an aggregate shock, as captured by an extreme downturn in a broad European banking sector index. For each bank stock (as well as the bank index), we calculated daily returns as the percentage changes in the return index. All series are expressed in local currency to prevent distortion by exchange rate fluctuations.

Before showing the estimated tail betas, we provide insight in the severity of the events that we are modelling. That is, we first report the unconditional Value-at-Risk levels or quantiles associated with probability $p = 0.04\%$. Doing so, we exploit one of the main benefits of modelling the entire tail of the (joint) distribution. We are looking at events that happen less frequently than the observed sample length. We summarize the findings on the unconditional Value-at-Risk levels in Table 1. In order to get these crash magnitudes, we first estimate the tail index for each individual series using the modified Hill estimator, Eq. (5). (Z is now a simple return series.) The magnitude of the daily loss for a given probability level can then be obtained using the inverse of Eq. (4); that is, $\widehat{q} = Z_{n-m,n}\left(\frac{m}{p \cdot n}\right)^{\frac{1}{\alpha}}$. Hence, lower probability events will cause an increase in the absolute value of the crash level, whereas events that occur more frequently (at least in terms of extreme value analysis) will lead to lower crash magnitudes.

$<$ **Insert Table 1 around here** $>$

Table 1 consists of three panels. Panel A contains information on the extreme losses of the European banking sector index for eleven (overlapping) time periods of six years. The first block of six years covers the period 1992-1997, the last period runs from 2002 to 2007. The first row reports the observed maximum daily loss in each six-year time period. The second line contains information on the estimated daily loss that happens with a probability of 0.04%. The estimated daily return fluctuates in the range of -5.3% and -9.3%. It is lowest (in absolute value) in the first period. From the second period onwards, the turbulent year 1998 enters the moving window. The magnitude of the estimated daily crashes (as well as the observed minimum) increases in absolute value. The relatively benign stock market conditions of 1999 and 2000 helped in mitigating the extreme losses. As a consequence the expected daily loss associated with an event that happens once every 10 years decreased from -9.1% to -6.5%. However, the (minimal) severity of a crash, which is expect to occur once every ten years, increases again from 2001 onwards to reach -9.3% in 1997-2002. The periods 1997-2002 and 1998-2003 are the periods with the largest extreme banking sector risk in the sample. In the last time period (2002-2007), we notice a drop in the observed minimum return as well as the estimated VaR of the European banking index. Notwithstanding that the turbulent period of 2007 enters the subperiod, the effect of dropping the returns in the year 2001 (compared to the previous period subsample) dominates. Note that in all but two periods, the estimated daily crash is worse than the observed minimal daily return. This is due to looking at events that are less frequent than the moving window of six years.

Panel B contains information on the time evolution as well as the cross-sectional dispersion in the daily losses of European bank stock returns that happen with a probability of 0.04%. The rows in panel B provide information on the variation in the Value-at-Risk across banks at each time span we consider. We report several percentiles as well as the mean and the standard deviation. The last row contains the number of banks we observe in that particular period of 6 years. Again, we report the results in eleven columns, one for each moving time frame of six years over the period 1992-2007. The median crash magnitude of the bank stocks exhibits a similar time pattern as the VaR of the European banking sector index. A first peak is reached over the period 1993-1998. In this period, the daily loss in market value associated with a 0.04% probability event exceeded 11.6% for half of the banks in the sample. In five of the eleven periods under consideration, the median daily VaR was also lower or equal to -11%. The mean VaR is almost always larger (in absolute value) than the median VaR and the gap between the two is larger in the initial sample years. Similar information can be extracted from the standard deviation. The standard deviation is indicative for the cross-sectional dispersion. The standard deviation has decreased from values around 0.08 to less than 0.04 (though increasing again in the last period, 2002-2007). This is caused both by a decrease in the crash magnitude of the riskiest banks and an increase in the riskiness of the (unconditionally) safest banks.

Panel C of Table 1 is constructed in a similar fashion as panel B and presents the expected shortfall. The expected shortfall is the average amount that is lost in a one-day period, assuming that the loss is lower than the 0.04^{th} percentile of the return distribution. The median expected shortfall fluctuates around daily losses of 15%, but there are large differences across banks.

The comparison of the estimated VaR (and the expected shortfall) of the European banking sector index (reported in panel A) and the mean (or median) crash level (expected shortfall) of the bank stock returns shows that most bank stocks have a higher downside risk potential than the banking index. This need not be surprising since we are comparing losses on a single asset with losses on a broad portfolio. The mean daily crash level is often 50% higher than the VaR of the European banking sector index. When looking at the percentiles over the different time periods, we observe that, in almost all time periods, 75% of the banks may fear a larger drop (expected shortfall) in its stock price than the equally unlikely crash (expected shortfall) in the banking sector portfolio. In the remainder of the paper, we investigate the properties and drivers of tail betas between bank stock returns and EU banking sector returns. In general, we will be interested in events that are as severe as the value-at-risk and expected shortfall figures reported in Table 1.

$<$ **Insert Table 2 around here** $>$

Table 2 contains information on the estimated tail-β. The table is structured in a similar fashion as panel B of Table 1. The different columns report values for various moving windows of six years. The first column covers the period 1992-1997. In subsequent columns, we always drop the first year of the sample and add another year at the end. The last subsample we consider is 2002-2007. The different lines in Table 2 provide an indication of the cross-sectional dispersion in the extreme systemic bank risk of the listed European banks. For each subsample, we report various percentiles, the mean and the standard deviation. The reported values are percentages. Hence, the mean of the European banks' tail-β in the first period indicates that there is a 7.4% probability that a European bank's stock price will crash, given that the banking market[7] as a whole crashes. To put it differently, given that there is a large downturn in the EU banking index, on average one out of 13 banks will experience an equally unlikely extreme stock price decline on that day. Recall that the level of the crashes does not need to be the same for the bank stock return and the conditioning asset (the European banking sector index). We rather look at crashes that have a similar probability of occurrence (set at 0.04%). In order to get some intuition on this number, it is interesting to relate this conditional probability to the results reported in Table 1. Given that there is a market correction in the European banking index of 5.3%, there is a 7.4% probability that the European banks will be confronted with an average fall in their share price of 11.7%.

[7]For each bank's tail beta, the value-weighted banking index excludes the respective bank.

The first and last column reveal that systemic bank risk is quite similar in both subsamples. Both the mean and the standard deviation of the tail-βs are roughly the same in the periods 1992-1997 and 2002-2007, with mean tail-βs around 7.4%. Nevertheless, in the intermediate periods, the dispersion and the level fluctuate. The mean tail-β more than doubles in the second subperiod. In four of the 11 subperiods, the tail beta exceeds 15%. Moreover, Table 1 shows that in these four periods, the unconditional VaR was also higher. Hence, not only is the tail beta higher, the magnitude of the crash would be more severe as well. In the other periods, the mean value of banks' extreme systemic risk approximates 10% or more. In each subsample, there is a lot of cross-sectional heterogeneity. The inter-quartile range (the difference between the 25th and 75th percentile) fluctuates over time but is often larger than 15%. In some subperiods, the range is even 20%. Furthermore, the mean tail beta exceeds the median at each point in time. This indicates that the distribution of the tail betas is skewed. It seems that many banks have low probabilities and are thus only moderately vulnerable to aggregated banking shocks. In fact, in each period, some banks have a tail-β (with respect to a broad European banking index) below 0.04%, which is the unconditional crash probability. This means that these bank stocks crash independently. Finally, Hartmann et al. (2006) report a mean tail-β of 19.4% for the 25 largest Euro-area banks. This is substantially higher than the mean tail-β we obtain in each subperiod. This is already a first indication that larger banks will have higher tail betas.

5 The bank-specific determinants of banking system stability

Table 2 reveals that the tail-βs can be quite different across banks and over time. This observation is of interest to bank supervisors who care about overall banking sector stability. However, next to knowing the evolution as well as the dispersion, it is even more interesting to get insight into the potential drivers of banking system stability. The drivers of cross-sectional heterogeneity in tail betas are analyzed by relating them to bank-specific variables. We have to take into account that the dependent variable is a probability. In such a case, the model $E(TAIL_\beta\,|X) = X\beta$ does not provide the best description of $E(TAIL_\beta\,|X)$. Since the observations are constrained within the unit interval, $[0,1]$, the effect of X on $TAIL_\beta$ cannot be constant over the range of X. Moreover, the predicted values from an OLS regression can never be guaranteed to be bound in the unit interval. In order to obtain that the fitted values after a comparative static analysis also result in probabilities, we need to employ a generalized linear model (Papke and Wooldridge, 1996; Kieschnick and McCullough, 2003),

$$E\left[TAIL_{\beta}\left|X\beta\right.\right] = g(X\beta) \tag{7}$$

where $g(.)$ is a link function such that $g(X\beta)$ is constrained within the unit interval. A natural candidate for the link function is the logistic transformation, $g(X\beta) = \frac{\exp(X\beta)}{1+\exp(X\beta)}$, also labelled the log odds ratio[8]. The independent variables, X, are averages over a six-year interval to match the time interval over which the dependent variable is estimated. We apply robust regression techniques[9] to control for outliers in the dataset. Moreover, in each regression, we include time dummies as well as country fixed effects to control for unobserved heterogeneity[10] in a given period or at the country level. Furthermore, the pooling of cross-sectional and time-series data implies that multiple observations on a given bank are not independent. Therefore, a robust estimation method that controls for groupwise heteroscedasticity is used. We cluster the standard errors at the country level[11]. Finally, for many banks, we obtain observations for several, but not all, subperiods, which

[8] Next to the logistic transformation, we also consider other appropriate transformations such as the probit and the (complementary) log-log link functions. The results are largely unaffected. All specifications yield a similar fit and statistical tests cannot discriminate in favour of a specific link function. We follow common practice and opt for the logistic link function. This link function is used most frequently when explaining fractional response variables.

[9] Robust regression is a form of iterated weighted least squares regression. Two types of weights are used: Huber (1981) weighting and biweighting. The two different kinds of weight are used because Huber weights can have difficulties with severe outliers, and biweights can have difficulties converging or may yield multiple solutions (Berk, 1990 and Stata 10, 2007). Using the Huber weights first helps to minimize problems with the biweights.

[10] We could also interact the time and country dummy to absorb the entire impact of variables that equally affect all banks in a country in a given period (such as: the macro-economic environment, the regulatory framework, the corporate default rate). However, some of these variables (especially regarding the regulatory framework) are not available over the period 1992-2007. Neglecting them may create an omitted variable bias. Interacting both dummy variables does not affect the coefficients of interest (or their significance).

We did not include bank-specific fixed effects, which correspond to de-meaning the variables at the bank level. However, low variability in the de-meaned values of the independent variables makes it more difficult (if not impossible) to estimate the coefficients and establish significant relationships. If the variance is low, these regressions may contain very little information about the parameters of interest, even if the cross-sectional variation is large (Arellano, 2003).

[11] The panel data at hand have three dimensions. This may result in residuals that are correlated across observations, which will cause OLS standard errors to be biased. Following Petersen (2009), we experiment with various cluster options: (i) unclustered, White standard errors; clustered standard errors at (ii) bank (iii) time or (iv) country level; clustering in two dimensions respectively (v) the bank and time dimension (vi) and the country and time level.

The standard errors obtained after clustering at the country level are much larger than the White standard errors and in general higher result in an unbalanced panel.

We are primarily interested in knowing how different financial activities affect banking system stability. Since the Second Banking Directive of 1989, banks are allowed to operate broad charters by diversifying functionally. Diversified banks provide a broad array of financial services, from granting loans, underwriting and distributing securities and insurance policies, to managing mutual funds and so on. Unfortunately, detailed data on banks' exposure to each of the aforementioned activities is in general not available. Therefore a pragmatic definition of functional diversification is used. More specifically, we will focus our analysis on the differential impact that different revenue sources may have on banks' tail betas. Total operating income is divided into four revenue classes. They are: net interest income, net commission and fee income, net trading income, and net other operating income. These sources of non-interest income capture all income from non-traditional intermediation. Moreover, this publicly available information is used by analysts and investors to assess the long-term performance potential and risk profile of a bank. We distinguish banks based on their observed revenue mix. Each type of revenue is expressed as a share of total operating income. As a result, the shares of net interest income, net commission and fee income, net trading income and net other operating income sum to one. Therefore, the share of net interest income is left out of the regression equation.

The baseline regression is specified as follows:

$$\begin{aligned} X\beta = \;& c + \beta_1 Net\ Commission\ Income + \beta_2 Net\ Trading\ Income \\ & + \beta_3 Net\ Other\ Operating\ Income + \beta_4 HHI_{REV} + \beta_5 HHI_{NON} \\ & + \delta \rho_{d\ln REV} + \widetilde{X}\gamma \end{aligned} \tag{8}$$

Hence, a significant coefficient on any of the other revenue shares ($\beta_1, \beta_2, \beta_3$) means that these activities contribute differently to banks' tail beta than do interest-generating activities. Following Mercieca et al. (2007) and Stiroh (2004b), we also account for diversification between the major activities interest income and non-

or almost equal to the standard errors obtained when clustered at the bank level. The importance of the time effect (after including time dummies) is small in this data set. Standard errors clustered at the time dimension are not higher than unclustered ones. Moreover, when we cluster the errors in two dimensions (bank-time or country-time), they are almost identical to the standard errors clustered only by the corresponding cross-section level (bank or country). An alternative way to estimate the regression coefficients and standard errors when the residuals are not independent is the Fama-MacBeth approach (Fama and MacBeth, 1973). The adjusted Fama-MacBeth standard errors are higher than the unadjusted. However, in general, they do not exceed the standard errors obtained when we cluster at the country level.

From this, we conclude that clustering the standard errors in the country dimension is the preferred approach.

interest income (HHI_{REV}), as well as within non-interest activities (HHI_{NON}). HHI_{REV} and HHI_{NON} are Herfindahl Hirschmann indices of concentration, where higher values of the index corresponds with more specialization in one of the constituent parts. Next to the specific source of revenue and the distribution of the revenue streams, we also examine the impact of the correlation between the various revenue streams and systemic banking risk. In a similar spirit as Stiroh (2004a), we compute bank-specific correlations between the growth rates of each pair of the revenue streams, represented by the vector $\rho_{d\ln REV}$ in Eq.(8). Hence, we include six correlation measures that capture whether a given bank's shocks to one type of income are typically accompanied by similar shocks to another type of income.

Besides investigating the impact of revenue diversity, we also include a number of other bank-specific characteristics, $\widetilde{X}$, that are similar in spirit to the constituent parts of the CAMELS rating used by US supervisory authorities. Summary statistics on the accounting variables are reported in Table 3. These variables capture strategic choices made by bank managers that may affect a bank's risk profile.

< Insert Table 3 around here >

The equity capital ratio and the liquid assets-to-total assets ratio are included to incorporate the possibility that better capitalized and more liquid institutions may be less vulnerable to market-wide events. We also take into account differences in bank efficiency by including the cost-to-income ratio. This ratio measures the overheads or costs of running the bank, the major element of which is normally salaries, as a percentage of income generated before provisions. Finally, bank size and bank profitability are also included. We include (the log of) bank size to allow for the possibility that larger banks may be more exposed to market-wide events. Bank profitability is included to control for a risk-return trade-off. Both measures are, to a large extent, outcomes of strategy choices made by banks and are hence highly correlated with the other control variables, and, more importantly, with the measures of functional diversification. Therefore, we orthogonalize them with respect to all other variables to derive the pure effects of size and profits[12]. As a result, the coefficients on the other variables capture the full effect on banks' tail-β. We also include two dummy variables in the baseline

[12]The profitability measure is regressed on all independent variables, except size. The residuals of this regression are used as a measure of excess profits above what is driven by banks' operational choices and are by definition orthogonal to these bank-specific variables. The natural logarithm of total assets is regressed on all independent variables including return on equity. The idea is to decompose bank size in an organic growth component and a historical size component, the residual.

regression, one for bank holding companies and one for large and complex banking groups[13] (LCBGs). LCBGs are banking groups whose size and nature of business is such that their failure and inability to operate would most likely have adverse implications for financial intermediation, the smooth functioning of financial markets, or other financial institutions.

The next subsection presents the estimation results of the general specification. In the subsequent subsection, we explore how the information content of tail-betas differs from that of central dependence measures. In the last subsection, we verify the appropriateness of the baseline equation from a methodological and an economic point of view.

5.1 Baseline regression results

The results[14] shown in column 1 of Table 4 reflect the relationships between various bank-specific variables and banks' tail beta measure. The tail beta measures the probability of observing a correction in a bank's equity return conditional on observing a large drop in the European Union banking sector index. From Table 4, it can be seen that interest income is less risky than all other revenue streams. This can be inferred from the observation that the coefficients of all other revenue shares are positive. This means that the alternative revenue streams have a bigger impact on banks' extreme risk measures than those originating from traditional intermediation activities. Put differently, the tail beta of a diversified bank is higher than the tail beta of a bank specialized in interest-generating activities. The coefficient on the share of trading income is the largest of the non-traditional revenue sources and its impact differs significantly from the other shares. The estimation results reveal that other indicators of bank specialization in traditional intermediation corroborate the finding that traditional banking activities result in lower systemic risk. Hence, we can conclude that banks that focus

[13] More information on how to obtain the set of LCBGs can be found in a special feature article of the ECB Financial Stability Review of December 2006. Based on a multiple indicator approach, i.e. cluster analysis, 33 banking groups are identified as LCBGs. 24 of these are located in the EU15, but not all of them are listed.

[14] The baseline results are obtained for a restricted sample of commercial banks and bank holding companies. We impose two restrictions on the sample used in the baseline. First, we eliminated non-diversified/specialized banks from the sample. That is, we only include banks with an interest income share between 10% and 90%. Furthermore, we also eliminate fast-growing banks. For these banks, the correlation between each pair of growth rates of the different revenue types may be biased and overstate the true degree of revenue correlation. In the robustness section, we document that these restrictions have little impact on the baseline results.

on lending activities are less exposed to systemic banking risk than diversified banks[15].

< **Insert Table 4 around here** >

The diversification measures do not enter the equation significantly. Apparently, having a more equally-balanced portfolio of revenue streams (either between interest and non-interest income or within non-interest income revenue) seems not to reduce or increase a bank's tail beta. On the other hand, the extent to which the growth rates of the various revenue streams are correlated does play an important role. The significant coefficients are positive, as portfolio theory predicts. Imperfectly correlated revenue streams should reduce bank risk. A low correlation between shocks to interest income and trading income reduces banks' tail-β significantly. Furthermore, a low correlation between shocks of any of the non-interest income types also contributes positively to overall banking system stability. These results imply that even though banks may have equal revenue shares, their risk profile may be substantially different depending on the correlation[16] between the revenue types.

The other bank-specific variables also reveal interesting relationships. Size is by far the most significant driver of banks' tail betas. Recall that the conditioning event is a crash in the European banking index, excluding the bank for which we compute the tail beta to avoid spurious results. Larger banks are inherently more exposed to many sectors in many countries and are hence more tied to European-wide shocks. Large drops in small banks' stock price are more likely to be idiosyncratic events or are more tied to local factors since small banks are predominantly active in their home country. In addition to the size effect, the dummy for Large and Complex Banking Groups is also associated with higher tail betas. In recent years, mergers, acquisitions and organic growth have meant that some of the largest and most complex financial groups have come to transcend national boundaries and traditionally defined businesslines. As a result, they have become a potential channel for the cross-border and cross-market transmission of financial shocks (Hawkesby, Marsh

[15]This conclusion is confirmed when including measures of market power and specialization in traditional banking markets in the regression. Banks with a higher interest margin or a higher loans-to-asset ratio are perceived to contribute less to banking system instability since higher values of these ratios reduce banks' tail betas. However, these variables are strongly correlated with the revenue shares, which affect both the magnitude and the precision of the estimated coefficients. Therefore we do not include them in the baseline specification.

[16]The correlations might be considered as generated regressors. Consequently, it is important to check whether the other coefficients and their standard errors are affected by including them. We also do the entire analysis without the correlation measures and observe that the coefficients and the standard errors of the other variables are remarkably unaltered.

and Stevens, 2007). Apparently, the banks at the heart of the financial system, which need to be monitored closely, contribute negatively to banking system stability. To check that the main results of the paper are not just a result of comparing small and large banks, we report in the robustness section results for various equally large subsamples (based on bank size). The capital-to-asset ratio exhibits the expected sign and is significant. A larger capital buffer increases a bank's contribution to banking system stability. Efficiency and liquidity do not enter the equation significantly. Banks that generate high profits ('in excess of their fundamentals') are much riskier. This mirrors the common risk-return trade-off. The causality in this relationship may, however, run in the other direction. Banks may gamble and increase their exposure to risky activities that may yield higher profits. A similar critique may hold for other relationships as well.

Next to return on equity, the equity-to-asset ratio may also suffer from reverse causality if banks' capital buffers are eroded from unexpected losses due to the more riskier income activity. Some of the relationships may be plagued by endogeneity. That is, the relationships could occur if riskier banks engage in non-traditional banking activities, rather than the reverse. Finally, given that the risk measure is based on stock market values, there might be a spurious relationship between trading income and tail betas. These possibilities can be checked by looking at the initial values of the ratio at the beginning of that six-year period rather than the average values over the six years. In Column 3 of Table 4, all accounting variables are measured as initial values. Some interesting conclusions can be drawn from this analysis. First, trading income is still significant, which indicates that trading income causally affects bank risk. The other alternative revenue shares also remain significant. Second, return on equity has a lower impact. This indicates that part of the risk-return relationship is due to the higher profits that risky activities generate. The bank's average profits over that period will be higher if a bank takes on more risk (as measured over a six year period). Nevertheless, the initial profitability level is also significantly and positively related to a bank's tail beta. Finally, a bank's initial capital ratio significantly reduces its exposure to systemic banking risk. The tail betas of banks that are financially strong banks at the beginning of the period are less affected by a crash in the EU banking sector index. In the last subsection, we document that these results are robust to potential reverse causality or endogeneity created by events such as mergers and acquisitions, delistings, or systemic crises.

Analyzing the economic impact of revenue diversification on banking system stability

Until now, we focussed the description of the results on the interpretation of the sign and the significance. To assess the magnitude of the coefficients and their economic impact we have to rely on fitted marginal effects. Both the (logistic) link function and the level of the variables affect the estimated effect of a change in one variable on the tail-β. That is:

$$\frac{\partial E\left[TAIL_{\beta}\,|X\beta\right]}{\partial X_i} = \frac{\partial g(X\beta)}{\partial X_i} = \widehat{\beta}_i \frac{\exp(X\widehat{\beta})}{\left(1+\exp(X\widehat{\beta})\right)^2} \tag{9}$$

In column 2 of Table 4, we report the marginal effects of each variable when the expression in Equation (9) is evaluated at the sample means. The marginal effects of the three non-interest revenue shares vary in the range of 0.13 to 0.38. The effect is largest if a bank reallocates revenues from Interest activities to Trading Income activities. To get more insight in this number, consider the following event. Over the sample period, the average share of net interest income in total income decreased by more than 12%. All else equal, this shift of 12% of total revenues from the interest activities to non-traditional banking activities yields an increase in the average bank's tail-β in the range of $1.5-4.6$ basis points. If an expansion into non-traditional banking is accompanied by a reduction in a bank's outstanding loans and interest margin, this may further increase the tail-β. Depending on the time period, an increase with 3.0 basis points corresponds to 30% of the median tail-β in 1994-1999 and almost 100% in 1999-2004.

A bank that keeps its revenue shares unchanged, but would be faced with less correlated interest income and trading income, will observe a drop in its tail-β. If this correlation drops from the sample mean (0.178) to that of the 5^{th} percentile ($-.767$), the tail beta will be almost 2.6 basis points lower. Hence, both the type of income and their correlation play an important role in increasing banking system stability.

Controlling for non-traditional banking activities, we discover that a larger capital buffer in financial institutions will exert a mitigating effect on systemic risk. An increase of the equity-to-assets ratio of 0.05 will result, all else equal, in a drop in the tail beta of 3 basis points. Bank size is by far the most important contributor to heterogeneity in tail risk. Consider two banks that only differ in size, one bank has the average size while the value of the total assets of the other bank is fixed at the 75^{th} percentile. The difference in tail-β exceeds 0.05. The larger bank will have, all else equal, a 5% higher probability of a large drop in its stock return if there is a large, negative shock to the European banking sector index. This increase equals a substantial proportion of the average tail-β. Depending on the time period, an increase with five basis points corresponds to 30% of the average tail-β in 1994-1999 and 50% of the average tail-β in 1999-2004. In addition, LCBGs have a tail beta that is, all else equal, 4.6 basis points higher.

The marginal effects are not constant; they depend on the values at which X is evaluated. Hence, although the argument within the link function is a parsimonious linear model, we are able to capture both non-linear relationships and interaction effects. On the one hand we can compute the marginal effect of a change in the variable X_i for different values of X_i while fixing the values of the other variables (at e.g. their sample mean). We learn that the implied effects differ substantially when they are assessed at other values than the mean. The marginal effect of a change in one of the revenue shares increases monotonously with the value of that variable. But the slope differs across the revenue shares. The impact of other operating income only increases moderately, largely due to the smaller range over which this revenue share is observed. The marginal effect of an increase in the trading income share on banks' tail beta is 0.38 at the sample mean (which is 6% of total income). The impact is around 0.30, if an otherwise equal bank only derives a small proportion (1%) of its income from trading activities. On the other hand, a bank with an even greater reliance on trading income, 16% of total operating income, will have a marginal effect of 0.60, which is two times larger than the bank in the latter case.

On the other hand, we are also able to assess the impact of a change in X_i for banks that only differ with respect to another variable X_j. Consider again the benchmark values of the average bank (as reported in column 2 of Table 4). At the mean trading income share, the marginal effect is 0.38. Since a larger capital buffer reduces banks' tail beta, the impact will be larger for less capitalized banks. The differential impact between the low and high capital ratio banks is 0.09 at the sample mean of trading income. This impact gap widens for banks that are more heavily involved in trading income generating activities and is for instance 0.13 when the trading income share is 16%. Put differently, in order to experience similar marginal effects of an increase in trading income, a better capitalized bank may already be more involved in this riskier revenue source. This confirms the presence of an interaction effect between the degree of capitalization and a bank's involvement in non-interest generating activities. Consequently, one could argue that regulatory capital requirements should be related to banks' reliance on trading income. Similarly, bank size is an important contributor in explaining differences in heterogeneity in bank tail risk. The marginal impact differs substantially for large and small banks. The interaction effects are even more apparent, especially for commission and trading income. The gap in marginal impacts of an increase in non-interest generating activities (in small versus large banks) widens substantially for larger shares of the associated revenue type.

5.2 Tail dependence versus central dependence

We are interested in assessing the extent to which individual banks are exposed to a severe aggregate shock, as captured by an extreme downturn in the EU banking sector index. For that purpose, multivariate extreme value analysis is a well-suited technique since it accounts for the fat tails that are inherent to stock prices and it is not tied to specific distributional assumptions. In general, most authors focus on risk during normal conditions. Dependency in the center of the distribution is typically measured using a firm's beta or a correlation coefficient, which both describe the sensitivity of an asset's returns to broad market or (bank) sector movements. While measures of dependence in the tails and the center are theoretically distinct concepts, they may share several features. For reasons of comparability with the tail-β, we measure banks' normal risk exposures to the banking index over moving windows of six years. The first period covers the years 1992-1997. In each subsequent subsample, we drop the observations of the initial sample year and add a more recent year of data. We analyze the information content of the dependence concepts and arrive at a number of interesting conclusions.

First, the rank correlation between the tail beta and the ordinary beta is very high. Across the eleven time windows of six years, it fluctuates in the range of 50% to 75%. Hence, banks with a large exposure to movements in the banking index in normal economic conditions will be more exposed to extreme movements as well. The high correlation implies that both dependence measures share an important component. Second, we establish significant relationships between non-traditional banking activities and systemic bank risk exposures (see Column 1 of Table 4 and 5). We run similar regressions, but substitute the dependent variable. The results are reported in Columns 2 of Table 5.

$<$ Insert Table 5 around here $>$

The tail beta is replaced as dependent variable by the OLS beta (obtained by regressing bank returns on returns on an EU banking index). We discover similar relationships. All non-interest generating activities increase the exposure of banks' stock returns to movements in the EU banking index. The impact of trading income is significantly larger than the impact of commission income and other operating income. Contrary to expectations, banks' OLS beta will be higher the more equal are the shares of interest and non-interest income. The coefficient on HHI_{REV} is negative and significant. The six measures of the correlation between shocks to pairs of income shares are all positively related to the OLS beta of a bank's stock return. Five of them are statistically significant. The largest potential for risk reduction can be obtained by combining imperfectly correlated interest and commission income generating activities. Furthermore, larger banks and less-capitalized banks have higher betas. In light of the previous finding, the high correlation between central and tail dependence measures, these observations are far from surprising. The more interesting issue is whether bank characteristics, and especially bank's income structure, can explain the residual heterogeneity in the tail-β that is not explained by central dependence measures.

Therefore, we add the OLS beta to the baseline regression (Column 3 of Table 5). Doing so, we want to decompose the effect of bank-specific variables on the tail betas into a direct effect and an indirect effect. The direct effects are the estimated relationships between a variable and the tail-beta. The indirect effect captures how a variable affects risk both in normal and extreme conditions and runs through the impact of the central dependence measure. Due to the large positive correlation, we expect and find a highly significant relationship between the traditional dependence measure and the tail beta. Hence, an increase in, for instance, the share of commission or trading income will indirectly result in an increase of the tail beta. If any of the bank-specific variables exhibit a significant[17] relationship with the tail beta, this implies that there is a direct effect that increases extreme bank risk in addition to the indirect effect.

When the central dependence measures are taken into account, we obtain that all non-traditional banking activities contribute positively to systemic banking risk. However, only the share of trading income in total income is significant at the conventional significance levels. Furthermore, a stronger correlation between shocks to other operating income and both other non-interest income sources, as well as between interest income and trading income, increases banks' tail-β. Measures of bank size and bank profitability are significant and hence enforce the positive indirect effect. Fourth, in column 4 Table 5, we report a joint effect[18], which is the sum of the direct (coefficients in Column 3) and indirect effect (coefficient on the central dependence measure times

[17]From Column 2 of Table 5, we learn that many bank-specific variables have a large partial correlation coefficient with the central dependence measure. This may create a multicollinearity problem and hence harms finding significant relationships by inflating the standard errors in Column 3 of Table 5. Therefore, we focus more on the magnitude of the coefficient rather than the significance level.

[18]The joint effects are, as expected, similar in magnitude to the coefficients reported in Column 1.

the estimated coefficients in Column 2). It is interesting to compare the direct effects, the coefficients in Column 3, with the joint effects in Column 4. For instance, the direct effect of an increase in commission income, trading income, or other operating income on a bank's extreme risk profile is larger than the indirect effect. The impact of correlated shocks also works predominantly via the direct effect. Reassuring for bank capital regulation is that the stabilizing impact of large capital buffers is stronger in turbulent times than in normal economic conditions.

To conclude, we discover a high correlation between banks' systemic risk exposures in normal and stress periods. Furthermore, the shift to non-traditional banking activities has increased banks' OLS beta and as a consequence their tail beta. However, there is also an additional and, for most variables, an even larger direct effect on banks' tail betas. The information content of tail betas differs from measures focussing on central dependence. In the robustness section, we also show that the information content of tail betas differs from other composite risk measures such as long-term debt ratings or equity return volatility.

5.3 Support for the baseline equation

Many banks are not included in all subperiods. Hence, the panel data set is unbalanced. If selection in the sample occurs randomly, then the results of the baseline regression are not subject to bias. However, some sources of sample selection are potentially non-random and may affect the estimated relationships. First, bank stocks that are traded infrequently are excluded since the risk measure will not be informative. Furthermore, some banks either entered the sample after an IPO or dropped out due to a delisting. These three events have in common that accounting data are available for the entire period but stock price information is not available or useful for the entire period 1992-2007. Another important source of unbalancedness are mergers and acquisitions. We examine the aforementioned selection issues simultaneously[19]. The estimation results are documented in Table 6. Column 1 contains the results for a substantially reduced sample. The sample

[19]We can also estimate a Heckman (1976) selection model for these events. Given that we consider multiple selection events, we implement a two-step procedure. Initially, we estimate three different selection equations (probit regressions). The dummy is one if that bank-time observation is included in the final sample and zero otherwise. Subsequently, we compute the Inverse Mills ratio (or selection hazard) for each selection equation and incorporate them in the baseline equation. We obtain that none of the Inverse Mills ratios is significant at the traditional significance levels. Accounting for non-randomness in the sample selection alters the marginal effects (slightly) but not the significance.

size reduces to 530 observations as a result of dropping banks that are involved in one or more of the selection criteria. In column 2, we report results for the initial sample size but include (not reported) dummy variables for the various potential sample selection problems. The results do not change qualitatively, an exception being the loss of significance of the other operating income share. However, in the smaller sample almost all coefficients are larger in absolute value. Regarding the dummy variables, we observe that banks whose shares are traded infrequently have lower tail betas. These banks are typically smaller banks, which strengthens the findings on bank size. To conclude, although the panel dataset is unbalanced, the sources of the missing values in the dataset do not affect the relationships of interest.

< Insert Table 6 around here >

Some European countries confronted a banking crisis[20] in the beginning of the nineties. Especially for the Scandinavian countries, the crises in the banking industry were severe in terms of output loss as a percentage of GDP. Given the focus on heterogeneity in banks' extreme risk profiles, these unusual events may drive the results. In column 3 of Table 6, we exclude a bank-time observation if this bank has been active in a country that experienced a banking crisis during one of the six years of that time frame. The results reported in Column 6 show that including the crisis periods does not affect the results (again, except for the share of other operating income in total income). The coefficients on the alternative revenue shares and the correlation coefficients are of a similar magnitude as those reported in Table 4, which further strengthens the stability of our findings.

The independent variables proxy strategic choices made by banks and capture information on capital, management, earnings and liquidity. Similar information might be contained in aggregated proxies of bank behavior, such as ratings or market-based information. In fact, the results in Table 5 document that there is indeed a relationship between bank's beta in normal and stress times, but that many independent variables have an additional impact. In columns 4-6, we include a rating on long-term bank debt, a measure of idiosyncratic volatility of banks' equity returns, and total volatility of bank equity returns. Concerning column 4 of Table 6, we follow Pop (2006) and construct the mean of long-term issuer ratings assigned by S&P, Moody's and Fitch. Before

[20] Information on the timing and magnitude of the crisis is obtained from the Worldbank Database of Banking Crises (Caprio, 2003). Six countries experienced a banking crisis during the sample period: Denmark (1992), Finland (1992-1994), France (1994-1995), Greece (1992-1995), Italy (1992-1995) and Sweden (1992-1995). Note that we only report the years that occur in the sample period, some crises started earlier.

averaging, the ratings are first converted to cardinal values using Pop's scale. The lower the cardinal value, the more creditworthy is the issuer. Including this rating reduces the sample size considerably to 360 observations. The coefficient on the long-term rating is measured imprecisely and is hence insignificant. More important, the results regarding the other coefficients are almost unaltered. Changes with respect to the baseline are the following: the coefficient on the other operating income share reduces considerably. Return on equity is only marginally significant, but this is due to the larger standard error because of the smaller sample rather than a change in the coefficient. All other coefficients are of equal size compared to the baseline regression without the rating, but the standard errors are larger. From column 5 and 6 of Table 6, we can infer that aggregate market-based measures of bank risk are not related to the tail beta. The results in both columns are almost exactly equal. The coefficient on the liquid assets to total assets ratio is slightly higher in the regression with total volatility. This, combined with a smaller standard error, yields a significant and positive relationship between this ratio and the tail beta. Apparently, additional measures of bank risk (total volatility, idiosyncratic volatility, rating on long term debt) do not enter the equation significantly nor do they affect the estimated coefficients on the other variables. This further underlines the fact that the information content of tail betas is different from other proxies of risk.

One of the most significant variables in determining tail betas is bank size. To check that the main results of the paper are not just a result of comparing small and large banks, we redo the analysis for various subsamples. We rank the banks according to size and split the sample in three equally large subsamples. The mean bank size of the smallest third is $7,989$ million euro. The average bank in the middle group has $54,025$ million euro of total assets. Average total assets in the group of large banks equals $241,680$ million euro. Performing the analysis on the three different subsamples does indeed yield further insights. We present the results in columns 1-3 of Table 7. First, many of the obtained results hold for each subsample. Larger banks, less capitalized banks, LCBGs and banks with a large share of trading income have higher tail betas. Second, the impact of commission income and other operating income on tail betas is significant for the subsets of small and medium-sized banks, but not for the subsample of the largest banks. For the largest banks, only trading income is perceived as a more risky revenue stream. Third, the impact of the correlation between pairs of revenue streams is largely similar across the three different subsamples. Fourth, the effect of cost-to-income and diversification (HHI-revenue) on tail betas differs substantially in the three subsamples. That is, we observe significant relationships with opposite signs, which is probably causing the insignificance of these variables in the overall sample. From this we can conclude that the baseline results are not merely a result of comparing small and large banks. Nevertheless, looking at various subsamples of banks with different size yields further insights into the determinants of systemic banking risk.

< Insert Table 7 around here >

The baseline results are obtained for a sample of commercial banks and bank holding companies. However, since the purpose of this research is to investigate the impact of diversification strategies on banking stability, we further imposed two restrictions on the sample used in the baseline. First, we eliminated non-diversified banks from the sample. That is, we only include banks with an interest income share between 10% and 90%. Banks not satisfying this criterion are categorized as too specialized. Furthermore, we also eliminate fast-growing banks. For these banks, the correlation between each pair of growth rates of the different revenue types may be biased and overstate the true degree of revenue correlation. Column 4 of Table 7 reports the results when we drop these restrictions and hence employ the full sample of commercial banks and bank holding companies. In this case, the sample size increases by 10% to 980 observations. All results established in Table 4 still hold. However, in the full sample the magnitude of the impact of the equity-to-asset ratio is substantially reduced (but still significant). In addition, we obtain that the Herfindahl Hirschmann index of the non-interest generating activities is negatively and significantly related to banks' tail-β. This unexpected result indicates that banks' risk profile will be improved if they focus their non-interest income. However, this is predominantly caused by a few banks that derive more than 90% of their income from non-traditional banking activities and should therefore be considered as outliers in a sample of commercial banks and BHCs.

Finally, we perform two robustness checks in which we zoom in on the dependent variable. First, we acknowledge that the dependent variable is an estimated variable and may hence be subject to measurement error. Variation in the sampling variance of the observations on the dependent variable will induce heteroscedasticity. Given the two-step procedure, we obtain information on part of this heteroscedasticity. We implement Hanushek's FGLS method (1974), which takes into account both the variance of the homoscedastic noise and the heteroscedasticity of the sampling errors. Note, however, that we now are no longer able to implement the weighting schemes we apply in the baseline regression to obtain robust regression results. We report the results in column 5 of Table 7. As in most robustness checks, the results are largely unaffected. Differences in significance with respect to the baseline (first column of Table 4) are only observed for two variables. The coefficients on other operating income and the correlation between shocks to trading and other operating income are significant in the baseline but not in this robustness check (though the estimates don't differ significantly from one another). We prefer robust regression methods over Hanushek FGLS method as the baseline, since the R-squared is much higher in the former compared to using FGLS. This provides an indication that controlling for outliers and robust standard errors is more important than taking into account the uncertainty introduced by the estimated dependent variable. Second, the paper deals with systemic banking risk and measures tail betas with respect to a European banking index. However, one could easily measure the tail beta of bank stock returns with respect to a general European market index. This measure would provide an indication of extreme systematic risk exposures. In the last column of Table 7, we replace our proxy of systemic risk with one of extreme systematic risk. That is, the dependent variable now captures the probability that a bank's equity return crashes, conditional on observing a market-wide correction. The results are very similar, which need not be surprising. First, given banks' central role in the economy, corrections in a banking sector index will most likely occur on days of broad market corrections and vice versa. Second, a large part of banks' commission and trading income stems from structured finance activities. A largely neglected feature of the securitization process is that it substitutes risks that are largely diversifiable for risks that are highly linked to events in the economy. Coval et al. (2009) document that the senior tranches of structured finance products have significantly higher systematic risk exposures, especially with respect to credit rating-matched, single-name counterparts. Consequently, these senior structured finance claims have the features of economic catastrophe bonds, as they are designed to default only in the event of extreme economic distress (Coval et al., 2008). A third explanation is offered by Pennacchi (2006), who models a bank's choice of investments when deposit insurance and capital standards are risk-based. His model predicts that banks would choose to sell credit protection for loans and bonds of firms with a high systematic risk of default. Moreover, deposit insurance provides a bank with incentives to engage more in the fee-generating business of providing loan commitments. However, the latter are the least profitable in the bad states of the world when firms' credit quality turns out to be low.

Both Coval et al. (2009) and Pennacchi (2006) argue that the existing capital requirements may have subsidized systematic risks. The existing requirements depend on credit risk assessments, either internal or by rating agencies, that focus on the probability of default and the loss given default. An important aspect of credit risk that is neglected by rating agencies and regulators is the timing of the default or the conditions in which default is likely to happen. Kupiec (2004) remarks that all of the New Basel Accord's proposed capital schemes contain incentives that may encourage banks to purposely concentrate on credits that are expected to default in recessions. Morever, banks may also be inclined to select the timing of default to enhance the value of their deposit insurance guarantee (Kupiec, 2004). Hence, as long as capital regulation or deposit insurance premiums fail to include a premium for systematic risk, banks will have an incentive to take extreme systematic risks, by engaging in non-interest activities.

6 Conclusion

The banking sector occupies a central role in every economy and is a particularly important sector for the stability of financial systems. As a result, central bankers and financial supervisors invest a great deal of resources in analyzing how to strengthen the financial system, including the system of financial regulation and supervision, to reduce the frequency and severity of future bouts of financial instability. Reliable indicators of banking system stability are of the utmost importance. In this paper, we employ a recent approach to assess banking system risk (Hartmann et al., 2006). This statistical approach assesses the joint occurrence of very rare events, such as severe banking problems. More specifically, the bank-specific systemic risk measure captures the probability of a sharp decline in a bank's stock price conditional on a crash in a European banking sector index. We discover considerable heterogeneity in banks' contributions to overall banking sector stability. This observation should not be surprising in light of some remarkable developments over the last decades. Substantial banking consolidation, the dismantling of the legal barriers to the integration of financial services, and technological evolution all affected the organizational design of banking firms. These developments initiated the emergence of large and complex banking organizations. Yet some banks continue to specialize in traditional intermediation activities or target local customers.

When relating the tail betas to bank-specific accounting variables, we can explain a fair amount of the cross-sectional dispersion in extreme bank risk. We establish that the shift to non-traditional banking activities increases banks' tail betas and thus reduces banking system stability because interest income is less risky than all other revenue streams. Moreover, the impact of the alternative revenue shares (commission and fee income, trading income, other operating income) do differ substantially from one another. Other indicators of bank specialization in traditional intermediation, such as the net interest margin and the loans-to-assets ratio, corroborate the finding that traditional banking activities are less risky. Hence, we can conclude that banks that profitably focus on lending activities contribute more to banking system stability than diversified banks. This questions the usefulness of financial conglomeration as a risk diversification device, at least in times of stock market turmoil. Retail banks, with a relatively high proportion of core deposits and loans in total assets, have a consistently lower systemic risk exposure. Moreover, as long as capital regulation or deposit insurance premiums fail to include a premium for systematic risk, banks will have an incentive to take extreme systematic risks by engaging in non-interest activities.

The established relationships bear implications for bank supervision. Bank size is by far the most significant driver of banks' tail betas. Some particularly thorny issues are raised by the existence of financial institutions that may be perceived as "too big to fail" and the moral hazard issues that may arise when governments intervene in a financial crisis. The latter could be perceived as an implicit expansion of the safety net and may exacerbate the problem of "too big to fail," possibly resulting in excessive risk-taking and still greater systemic risk in the future. Moreover, since the large banks are more exposed to European-wide (banking) shocks and economic conditions, their prudential supervision needs to take that feature into account. In Europe, increasing banking sector integration initiated by directives that led to the single market for financial services further complicated the tasks of national and supranational supervisors. This will be even more the case when banks further increase their cross-border activities, which strengthens the need for an integrated European supervisor for internationally operating banks. For the locally operating banks, supervision at the country level should suffice to assess the implications of their risk profile.

In addition, the results are interesting in light of the third pillar of Basel II. Market participants, in addition to armies of regulators, will do some of the work in assessing the overall risk position of the bank. A larger capital buffer decreases a bank's exposure to extreme shocks. This finding is expected and underlines the importance of capital adequacy as a signal of bank creditworthiness. Furthermore, a more complete and coherent disclosure of the different revenue streams facilitates a better understanding of the risks being taken by different institutions. The debate on the optimality and desirability of universal banking and financial conglomerates is still unsettled. Some blame the recent banking crisis of 2008 on a lack of regulation of certain financial activities or even deregulation with respect to the combination of commercial and investment banking. While it is unknown to what extent the crisis could have been avoided by more regulation, more disclosure and transparency of the different financial activities and the associated revenue streams would have helped in mitigating, identifying, and resolving many problems. Therefore, in European banking, steps need to be taken in order to get a more detailed and consistent picture of the underlying components of non-interest revenue, especially with respect to commission and fee income. The US reporting requirements, which since March 2001 include a 12-item distinction of non-interest income, may be a useful benchmark.

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Table 1: Unconditional Value at Risk and Expected Shortfall

Panel A: returns on European banking sector equity index

	1992-1997	1993-1998	1994-1999	1995-2000	1996-2001	1997-2002	1998-2003	1999-2004	2000-2005	2001-2006	2002-2007
Observed minimum return	-0.037	-0.058	-0.058	-0.058	-0.079	-0.079	-0.079	-0.079	-0.079	-0.079	-0.059
VaR(EU-bankindex) with p=0.04%	-0.053	-0.091	-0.069	-0.065	-0.082	-0.093	-0.092	-0.076	-0.079	-0.074	-0.059
ES (EU-bankindex) with p=0.04%	-0.093	-0.162	-0.108	-0.098	-0.129	-0.133	-0.134	-0.110	-0.116	-0.107	-0.079

Panel B: VaR (with p=0.04%) of European bank stock returns

	1992-1997	1993-1998	1994-1999	1995-2000	1996-2001	1997-2002	1998-2003	1999-2004	2000-2005	2001-2006	2002-2007
5th percentile	-0.236	-0.273	-0.243	-0.175	-0.176	-0.162	-0.169	-0.190	-0.183	-0.183	-0.181
10th percentile	-0.186	-0.210	-0.171	-0.152	-0.160	-0.157	-0.155	-0.153	-0.166	-0.150	-0.154
25th percentile	-0.126	-0.143	-0.138	-0.129	-0.129	-0.137	-0.138	-0.125	-0.132	-0.130	-0.120
50th percentile	-0.093	-0.116	-0.110	-0.108	-0.111	-0.115	-0.112	-0.100	-0.101	-0.103	-0.094
75th percentile	-0.078	-0.091	-0.089	-0.083	-0.083	-0.086	-0.086	-0.071	-0.080	-0.078	-0.073
90th percentile	-0.058	-0.071	-0.066	-0.063	-0.062	-0.070	-0.064	-0.056	-0.057	-0.054	-0.054
95th percentile	-0.051	-0.058	-0.054	-0.043	-0.049	-0.053	-0.059	-0.049	-0.045	-0.047	-0.046
mean	-0.117	-0.135	-0.123	-0.109	-0.116	-0.112	-0.113	-0.106	-0.106	-0.107	-0.106
standard deviation	0.080	0.104	0.081	0.043	0.075	0.035	0.038	0.045	0.045	0.044	0.068
number of observations per time period	85	96	94	91	90	94	96	102	113	114	110

Panel C: Expected Shortfall (with p=0.04%) of European bank stock returns

	1992-1997	1993-1998	1994-1999	1995-2000	1996-2001	1997-2002	1998-2003	1999-2004	2000-2005	2001-2006	2002-2007
5th percentile	-0.358	-0.403	-0.362	-0.262	-0.264	-0.241	-0.251	-0.272	-0.285	-0.275	-0.270
10th percentile	-0.301	-0.318	-0.284	-0.235	-0.231	-0.226	-0.230	-0.235	-0.239	-0.235	-0.222
25th percentile	-0.196	-0.221	-0.205	-0.189	-0.189	-0.197	-0.201	-0.187	-0.200	-0.198	-0.188
50th percentile	-0.146	-0.176	-0.161	-0.152	-0.159	-0.162	-0.159	-0.137	-0.148	-0.155	-0.141
75th percentile	-0.110	-0.134	-0.129	-0.119	-0.116	-0.115	-0.117	-0.108	-0.108	-0.115	-0.103
90th percentile	-0.092	-0.107	-0.098	-0.086	-0.085	-0.092	-0.091	-0.078	-0.074	-0.077	-0.069
95th percentile	-0.068	-0.088	-0.080	-0.052	-0.065	-0.085	-0.077	-0.063	-0.056	-0.054	-0.058
mean	-0.176	-0.202	-0.182	-0.160	-0.165	-0.161	-0.161	-0.153	-0.156	-0.159	-0.156
standard deviation	0.110	0.134	0.108	0.068	0.099	0.056	0.056	0.067	0.067	0.068	0.094
number of observations per time period	85	96	94	91	90	94	96	102	113	114	110

Note: this table contains information on the unconditional Value at Risk and Expected Shortfall for different time periods. Panel A provides the results for the European banking sector equity index. Panels B and C report the time evolution as well as the cross-sectional heterogeneity across the set of listed European banks. The unconditional VaR is measured using univariate extreme value analysis. The crash magnitude or VaR corresponds with an event that occurs with a probability of 0.04%. Panel C presents the expected shortfall that corresponds with an event that occurs with a probability of 0.04%.

Table 2: Tail beta

Tail-beta of European bank stock returns w.r.t. a European banking sector index											
	1992-1997	1993-1998	1994-1999	1995-2000	1996-2001	1997-2002	1998-2003	1999-2004	2000-2005	2001-2006	2002-2007
5th percentile	0.03	0.04	0.02	0.02	0.13	0.19	0.16	0.06	0.02	0.07	0.03
10th percentile	0.05	0.13	0.11	0.34	0.47	0.78	0.45	0.13	0.16	0.14	0.19
25th percentile	0.27	2.08	1.96	2.18	3.71	2.75	2.30	0.56	0.73	1.03	0.99
50th percentile	2.35	11.57	10.24	10.81	9.90	7.71	8.53	3.82	2.85	3.66	2.60
75th percentile	8.87	29.68	25.64	25.19	28.94	20.97	20.86	15.35	15.17	16.16	7.06
90th percentile	23.87	48.54	41.32	39.05	42.21	31.60	31.87	29.39	29.96	31.85	22.18
95th percentile	27.36	57.08	53.46	50.17	52.02	42.90	41.53	48.64	47.22	44.81	39.07
mean	7.38	17.65	16.93	15.86	17.46	13.27	12.87	10.68	9.95	11.15	7.71
standard deviation	13.00	18.92	17.67	15.88	17.08	13.43	13.10	14.96	14.32	14.80	12.64
number of observations per time period	87	97	96	91	91	94	96	106	118	122	111

Note: this table contains information on the tail-beta for the set of listed European banks. Tail beta measures the probability of a crash in bank stock conditional on a crash in a European banking sector index. The tail-betas are obtained using the Ledford and Tawn approach (1996). The table reports the time evolution as well as the cross-sectional heterogeneity across the set of listed European banks. The numbers are in percentages. The crashes occur with a probability of 0.04%.

Table 3: Summary statistics bank ratios

	mean	standard deviation	5th percentile	25th percentile	median	75th percentile	95th percentile
Interest Income	0.569	0.175	0.177	0.498	0.616	0.681	0.771
Commission and Fee income	0.278	0.140	0.126	0.203	0.258	0.310	0.581
Trading Income	0.060	0.076	0.000	0.012	0.036	0.083	0.212
Other Operating Income	0.081	0.108	0.000	0.018	0.045	0.099	0.291
Diversification of non-interest income	0.604	0.156	0.402	0.489	0.567	0.722	0.889
Diversification of revenues: interest vs non-interest income	0.570	0.082	0.501	0.516	0.544	0.587	0.734
Correlation (interest income growth,commission income growth)	0.139	0.568	-0.785	-0.357	0.192	0.655	0.914
Correlation (interest income growth,trading income growth)	-0.026	0.481	-0.810	-0.409	-0.036	0.344	0.785
Correlation (interest income growth,other operating income growth)	-0.005	0.475	-0.769	-0.384	-0.017	0.364	0.783
Correlation (commission income growth,trading income growth)	0.095	0.447	-0.631	-0.243	0.074	0.440	0.846
Correlation (commission income growth, other operating income growth)	0.095	0.460	-0.711	-0.232	0.125	0.443	0.841
Correlation (trading income growth, other operating income growth)	0.026	0.473	-0.781	-0.331	0.002	0.365	0.814
log Total Assets	9.447	2.267	6.065	7.646	9.293	11.140	13.226
Equity-to-Assets	0.082	0.086	0.031	0.047	0.060	0.085	0.173
Cost-to-Income	0.642	0.145	0.415	0.567	0.635	0.715	0.871
Loans-to-Assets	0.549	0.183	0.162	0.455	0.564	0.674	0.826
Return on Equity	0.126	0.089	0.000	0.091	0.134	0.169	0.233
Liquid Assets-to-Assets	0.186	0.123	0.040	0.095	0.156	0.248	0.429
Idiosyncratic volatility of bank return	0.017	0.008	0.009	0.013	0.016	0.020	0.031
Total volatility of bank return	0.019	0.008	0.009	0.014	0.018	0.023	0.031
Rating on Long Term debt	4.998	1.521	2.877	3.934	4.974	6.000	7.500

Note: this table contains information on the bank-specific variables used in this paper. The ratios are computed as averages over each 6 year period. The first set of rows contains information on the different revenue shares. The next block contains info on the revenue-based measures of functional diversification. The third block provides information on the distribution of correlation between any pair of growth rates of the four types of bank revenue. The last nine rows provide summary statistics on the other bank-specific variables. The summary statistics provided are computed for the unbalanced panel of bank-time observations of the commercial banks and bank holding companies.

Table 4: Drivers of heterogeneity in banks' tail beta

	Baseline regression (banking system risk)	Marginal effects at sample mean	Baseline regression (all ratios measured as intial values)
Constant	-3.1393***		-3.6687***
	[0.5209]		[0.3541]
Commission and Fee income	2.4418***	0.169	3.1781***
	[0.7708]		[0.6230]
Trading Income	5.5181***	0.382	3.8816***
	[1.3802]		[0.7666]
Other Operating Income	1.8573*	0.129	2.5810***
	[1.0027]		[0.6829]
	-0.5085	-0.035	-0.7630***
Diversification of non-interest revenues	[0.6087]		[0.2379]
Diversification of revenues: interest vs	-0.6503	-0.045	-0.6957
non-interest income	[1.1152]		[0.7621]
Correlation (interest income	-0.0826	-0.006	-0.0367
growth,commission income growth)	[0.1167]		[0.1133]
Correlation (interest income	0.3985***	0.028	0.4280***
growth,trading income growth)	[0.1092]		[0.1266]
Correlation (interest income growth,other	-0.0762	-0.005	-0.1645
operating income growth)	[0.1433]		[0.1288]
Correlation (commission income	0.0122	0.001	0.0104
growth,trading income growth)	[0.1084]		[0.1063]
Correlation (commission income growth,	0.2374***	0.016	0.1826*
other operating income growth)	[0.0669]		[0.0957]
Correlation (trading income growth, other	0.2232***	0.015	0.1825***
operating income growth)	[0.0626]		[0.0446]
Size	0.4877***	0.034	0.4789***
	[0.0335]		[0.0385]
Equity-to-Assets	-8.7110***	-0.604	-6.0362***
	[1.3743]		[0.8191]
Cost-to-Income	-0.4317	-0.030	0.2210*
	[0.3718]		[0.1241]
Return on Equity	1.9733***	0.137	0.3312***
	[0.4506]		[0.0707]
Liquid assets-to-Assets	0.4367	0.030	-0.1416
	[0.2717]		[0.4825]
Large and Complex Banking Group	0.5656***	0.046	0.4747**
dummy	[0.1912]		[0.2155]
	-0.092	-0.006	-0.1028
Bank Holding Company dummy	[0.1977]		[0.1944]
Observations	879		888
R-squared	0.787		0.781
AIC	0.547		0.556
Standard errors in brackets (clustered at country level)			
* significant at 10%; ** significant at 5%; *** significant at 1%			

Note: The first column reports the results for the baseline regression. In this regression, the dependent variable, the tail-β, provides an indication of systemic risk of the banking sector over a period of six year. The tail-beta is a probability and hence bound between [0,1]. Therefore, we employ a generalized linear model, estimated using quasi-maximum likelihood. The independent variables are averages over a six year interval to match the time interval over which the dependent variable is estimated. We apply robust regression techniques to mitigate the effect of outliers in the dataset. In each regression, we include time dummies as well as country fixed effects. Standard errors take into account groupwise heteroscedasticity. The second column contains the marginal effects of the coefficients in the first column. The marginal effects are evaluated at the sample mean of the ratios. The third column reports results for variations on the benchmark equation. If a coefficient is reported in a grey box, this means that this ratio is measured as the initial value at the beginning of that period (rather than being an average over that six year period).

Table 5: The information content of the tail beta versus the traditional OLS beta

	Baseline	Determinants of OLS beta	Baseline with OLS beta as additional regressor	Joint Effects
Constant	-3.1393***	0.5254***	-3.3685***	
	[0.5209]	[0.1668]	[0.5516]	
Commission and Fee income	2.4418***	0.3785**	1.438	1.8268
	[0.7708]	[0.1754]	[0.9930]	
Trading Income	5.5181***	2.5246***	3.0623**	5.6553
	[1.3802]	[0.3796]	[1.3416]	
Other Operating Income	1.8573*	0.4577***	0.7948	1.2649
	[1.0027]	[0.1777]	[0.9673]	
	-0.5085	0.0277	-0.6021	-0.5736
Diversification of non-interest revenues	[0.6087]	[0.1079]	[0.5228]	
Diversification of revenues: interest vs	-0.6503	-0.5305*	-0.4541	-0.9990
non-interest income	[1.1152]	[0.3224]	[0.8731]	
Correlation (interest income	-0.0826	0.0890***	-0.2365**	-0.1451
growth,commission income growth)	[0.1167]	[0.0190]	[0.1091]	
Correlation (interest income	0.3985***	0.0432***	0.3671***	0.4115
growth,trading income growth)	[0.1092]	[0.0130]	[0.1162]	
Correlation (interest income growth,other	-0.0762	0.0351***	-0.1111	-0.0750
operating income growth)	[0.1433]	[0.0110]	[0.1365]	
Correlation (commission income	0.0122	0.0321**	0.0174	0.0504
growth,trading income growth)	[0.1084]	[0.0162]	[0.0870]	
Correlation (commission income growth,	0.2374***	0.0593***	0.1466***	0.2075
other operating income growth)	[0.0669]	[0.0209]	[0.0565]	
Correlation (trading income growth, other	0.2232***	0.0129	0.2193***	0.2325
operating income growth)	[0.0626]	[0.0100]	[0.0681]	
Size	0.4877***	0.1369***	0.3091***	0.4497
	[0.0335]	[0.0137]	[0.0544]	
Equity-to-Assets	-8.7110***	-1.5037***	-6.6993***	-8.2438
	[1.3743]	[0.4224]	[1.7386]	
Cost-to-Income	-0.4317	0.0119	-0.291	-0.2788
	[0.3718]	[0.1080]	[0.3942]	
Return on Equity	1.9733***	0.0894	1.6645***	1.7563
	[0.4506]	[0.0905]	[0.5186]	
Liquid assets-to-Assets	0.4367	-0.3060*	0.4519	0.1376
	[0.2717]	[0.1660]	[0.3540]	
Large and Complex Banking Group	0.5656***	0.3142***	0.4718**	0.7945
dummy	[0.1912]	[0.1089]	[0.1966]	
	-0.092	-0.0983**	-0.0901	-0.1911
Bank Holding Company dummy	[0.1977]	[0.0427]	[0.2207]	
OLS beta			1.0271***	
			[0.2778]	
Observations	879	869	879	
R-squared	0.787	0.874	0.800	
AIC	0.547	-0.983	0.545	
Standard errors in brackets (clustered at country level)				
* significant at 10%; ** significant at 5%; *** significant at 1%				

Note: The table presents information on the differential impact of various bank characteristics on the tail beta and the OLS beta, which captures dependency in normal times. The first column reports the results for the baseline regression. In this regression, the dependent variable, the tail-β, provides an indication of systemic banking risk over a period of six year. The tail-beta is a probability and hence bound between [0,1]. Therefore, we employ a generalized linear model, estimated using quasi-maximum likelihood. The independent variables are averages over a six year interval to match the time interval over which the dependent variable is estimated. We apply robust regression techniques to mitigate the effect of outliers in the dataset. In each regression, we include time dummies as well as country fixed effects. Standard errors take into account groupwise heteroscedasticity. Columns 2 to 4 report information when information in the OLS beta, used to measure the normal dependence between bank stock returns and the returns on a European banking sector index, is taken into account. Column 2 reports the results for the drivers of the OLS beta. In column 3, this OLS beta is added to the baseline regression. In column 4, we report the joint effects. The joint effect of a bank characteristic is the sum of a direct effect on banks' tail beta (coefficient in column 3) and an indirect effect via the traditional dependence measure (last coefficient of column 3 multiplied with coefficient in column 2).

Table 6: Support for the baseline equation

	Exclude banks that have been involved in M&A, IPO, Delisting or which share is illiquid	Baseline plus (not reported) dummies for several events (M&A, IPO, Delisting or illiquid share)	Exclude banking crisis from sample	Baseline + Long term debt rating	Baseline + idiosyncratic volatiliy	Baseline + total volatiliy
Constant	-2.4278***	-3.0211***	-3.2794***	-1.3127	-3.2606***	-3.1155***
	[0.8892]	[0.6493]	[0.5129]	[1.1685]	[0.5872]	[0.5523]
Commission and Fee income	1.7586**	2.3406***	2.3579***	2.9273***	2.4144***	2.4410***
	[0.7069]	[0.7240]	[0.6965]	[0.4526]	[0.7601]	[0.7727]
Trading Income	6.5430*	4.4225***	5.0058***	4.3940*	5.5000***	5.5034***
	[3.7180]	[1.4582]	[1.3271]	[2.2589]	[1.3707]	[1.4363]
Other Operating Income	1.4099	1.5539	1.5739	0.8171	1.8246*	1.8569*
	[1.4698]	[1.0321]	[1.0196]	[0.9934]	[1.0251]	[0.9972]
Diversification of non-interest revenues	-0.7101	-0.7909	-0.5195	-0.5421	-0.4926	-0.5117
	[0.7341]	[0.5514]	[0.5578]	[0.7642]	[0.6194]	[0.6088]
Diversification of revenues: interest vs non-interest income	-1.1357	-0.4758	-0.4733	-1.9701	-0.5283	-0.6738
	[2.2077]	[1.0225]	[1.0825]	[2.2664]	[1.1768]	[1.0954]
Correlation (interest income growth,commission income growth)	-0.0645	-0.0914	-0.0547	-0.3000**	-0.0713	-0.0855
	[0.1144]	[0.1081]	[0.1261]	[0.1303]	[0.1099]	[0.1106]
Correlation (interest income growth,trading income growth)	0.2334*	0.3951***	0.3946***	0.3652***	0.3982***	0.3982***
	[0.1369]	[0.0806]	[0.1218]	[0.1248]	[0.1067]	[0.1102]
Correlation (interest income growth,other operating income growth)	0.0417	-0.0753	-0.073	-0.0105	-0.079	-0.0759
	[0.1321]	[0.1440]	[0.1492]	[0.1311]	[0.1442]	[0.1432]
Correlation (commission income growth,trading income growth)	-0.0597	0.0235	0.0175	-0.0759	0.0133	0.0122
	[0.1127]	[0.0875]	[0.1201]	[0.1121]	[0.1115]	[0.1076]
Correlation (commission income growth, other operating income growth)	0.0629	0.2632***	0.2345***	0.2412**	0.2375***	0.2368***
	[0.1073]	[0.0810]	[0.0797]	[0.1051]	[0.0670]	[0.0671]
Correlation (trading income growth, other operating income growth)	0.4556***	0.1895***	0.2523***	0.1662**	0.2254***	0.2231***
	[0.1043]	[0.0583]	[0.0545]	[0.0833]	[0.0665]	[0.0623]
Size	0.4393***	0.4280***	0.4878***	0.4687***	0.4892***	0.4865***
	[0.0721]	[0.0382]	[0.0333]	[0.0665]	[0.0346]	[0.0360]
Equity-to-Assets	-7.6135***	-6.9815***	-8.1538***	-8.9409*	-8.7349***	-8.6888***
	[2.1831]	[1.1564]	[1.4975]	[4.8348]	[1.4627]	[1.4398]
Cost-to-Income	-0.9044	-0.8809**	-0.1861	-0.0928	-0.2673	-0.4587
	[0.8112]	[0.3958]	[0.3778]	[0.6349]	[0.3591]	[0.3756]
Return on Equity	1.5925**	1.8279***	2.5836***	2.2221	1.7789***	2.0034***
	[0.6713]	[0.5408]	[0.4715]	[1.3779]	[0.5371]	[0.4873]
Liquid assets-to-Assets	0.3475	1.2256**	0.2919	-1.1114	0.3616	0.4482*
	[1.1858]	[0.4988]	[0.3738]	[0.8585]	[0.3089]	[0.2628]
Large and Complex Banking Group dummy	0.6518***	0.6719***	0.5685***	0.5474*	0.5465***	0.5664***
	[0.2184]	[0.1495]	[0.2067]	[0.2801]	[0.2034]	[0.1936]
Bank Holding Company dummy	-0.7089***	-0.2095	-0.058	0.0286	-0.0756	-0.0948
	[0.2486]	[0.1563]	[0.1960]	[0.2641]	[0.1989]	[0.2004]
Total volatility of bank equity return						1.518
						[7.2299]
Idiosyncratic volatility of bank equity return					-9.1489	
					[10.5181]	
Long term debt rating				-0.002		
				[0.1770]		
Observations	530	879	795	360	879	879
R-squared	0.753	0.799	0.791	0.828	0.788	0.787
AIC	0.607	0.556	0.561	0.818	0.549	0.549

Standard errors in brackets (clustered at country level)

* significant at 10%; ** significant at 5%; *** significant at 1%

Note: The table presents information on the stability of the baseline results in various subsamples. In column 1, we redo the analysis of the baseline regression but exclude (i) banks whose shares have been illiquid in previous sample periods (ii) banks that go public and banks that are delisted (iii) banks that constitute the separate entities before the M&A and without the resulting new entity after the M&A.

In column 2, we use the baseline sample but include (not reported) dummies for each of the aforementioned events. In Column 3, we exclude a bank-time observation if the banking industry in the associated country experiences a banking crisis in one of the 6 years of that timeframe. In column 4-6 we control for various proxies of bank risk. We include respectively the rating on long-term bank debt (column 4), the idiosyncratic component of bank equity return volatility (column 5) and total bank equity return volatility (column 6). In the regressions, the dependent variable, the tail-β, provides an indication of systemic banking risk over a period of six year. The tail-beta is a probability and hence bound between [0,1]. Therefore, we employ a generalized linear model, estimated using quasi-maximum likelihood. The independent variables are averages over a six year interval to match the time interval over which the dependent variable is estimated. We apply robust regression techniques to mitigate the effect of outliers in the dataset. In each regression, we include time dummies as well as country fixed effects. Standard errors take into account groupwise heteroscedasticity.

Table 7: Further support for the baseline equation

	Baseline (small banks)	Baseline (medium banks)	Baseline (large banks)	Baseline sample + fast-growing banks + Specialized banks	Baseline (Hanushek standard errors)	Extreme systematic risk
Constant	-5.5496***	-1.2993	-4.5963***	-3.2628***	-0.9549	-3.1386***
	[1.1619]	[1.0741]	[0.8644]	[0.3602]	[0.8329]	[0.5403]
Commission and Fee income	3.6649***	3.7221***	0.5003	2.5734***	1.7506**	2.1528***
	[1.1585]	[1.0238]	[1.1745]	[0.4346]	[0.8661]	[0.6994]
Trading Income	5.0449	5.8982***	3.0989**	3.2942***	3.6741***	4.6244***
	[3.3513]	[1.3760]	[1.5210]	[1.0463]	[1.0159]	[1.3042]
Other Operating Income	2.1672*	2.6513**	-0.4018	1.9706**	0.5302	1.8423**
	[1.2240]	[1.0879]	[1.7199]	[0.8934]	[0.9481]	[0.8260]
Diversification of non-interest	-4.1463***	0.2957	-0.6903	-2.5071***	0.1037	-0.7313
revenues	[1.1580]	[0.6565]	[0.7550]	[0.5281]	[0.8648]	[0.6705]
Diversification of revenues: interest	5.0057***	-2.7356*	2.8577**	1.1453	-2.4845	0.0495
vs non-interest income	[1.3075]	[1.6022]	[1.1637]	[0.9309]	[2.1001]	[1.1059]
Correlation (interest income	0.5749***	-0.0809	-0.0533	-0.0227	-0.0921	0.054
growth,commission income growth)	[0.1054]	[0.0925]	[0.1676]	[0.1174]	[0.1080]	[0.1004]
Correlation (interest income	0.2604	0.6553**	0.3356**	0.2850**	0.5632***	0.3272***
growth,trading income growth)	[0.2582]	[0.2555]	[0.1475]	[0.1331]	[0.0816]	[0.0913]
growth,other operating income	-0.1431	-0.0767	-0.0667	-0.2184	-0.1732	-0.0987
growth)	[0.1514]	[0.1917]	[0.1722]	[0.1417]	[0.1507]	[0.1607]
Correlation (commission income	-0.078	-0.0164	-0.1133	0.1139	-0.0698	0.0806
growth,trading income growth)	[0.1382]	[0.1130]	[0.1109]	[0.1055]	[0.1484]	[0.0731]
growth, other operating income	0.5637***	0.4211***	0.1577***	0.1065	0.3036***	0.3397***
growth)	[0.1471]	[0.0881]	[0.0584]	[0.1011]	[0.0297]	[0.0922]
Correlation (trading income growth,	0.4604***	-0.1038	0.2027**	0.2278***	0.209	0.1506
other operating income growth)	[0.1218]	[0.0675]	[0.0842]	[0.0562]	[0.1453]	[0.0996]
Size	1.1203***	0.4105***	0.4343***	0.4810***	0.4509***	0.4814***
	[0.1536]	[0.1265]	[0.0614]	[0.0382]	[0.0338]	[0.0516]
Equity-to-Assets	-3.5325**	-6.3578**	-10.6192***	-2.2823***	-8.4255***	-6.8113***
	[1.6368]	[2.8732]	[2.9191]	[0.7466]	[2.0196]	[1.9231]
Cost-to-Income	2.0297***	-1.8450***	0.1138	-0.7133**	-0.6857	-1.3576***
	[0.6997]	[0.6458]	[0.3221]	[0.3511]	[0.4645]	[0.5260]
Return on Equity	6.0850***	1.5009	3.0321***	1.3402***	2.1381***	1.9329**
	[1.6402]	[1.6558]	[0.8301]	[0.5190]	[0.5675]	[0.8432]
Liquid assets-to-Assets	1.3744	0.7704***	0.9416***	0.3194	1.5760***	1.1439***
	[1.2514]	[0.2895]	[0.3573]	[0.3762]	[0.5791]	[0.3754]
Large and Complex Banking Group dummy		1.2343***	0.8166**	0.3450*	0.8244***	0.5226*
		[0.2240]	[0.3683]	[0.1996]	[0.2778]	[0.2966]
Bank Holding Company dummy	-0.3269	0.0141	0.135	-0.1619	-0.0278	-0.1306
	[0.7902]	[0.3791]	[0.2047]	[0.1902]	[0.1933]	[0.2529]
Observations	288	294	295	980	886	876
R-squared	0.857	0.827	0.845	0.756	0.678	0.775
AIC	0.442	0.727	0.933	0.536	0.742	0.537

Standard errors in brackets (clustered at country level)
* significant at 10%; ** significant at 5%; *** significant at 1%

Note: The table presents information on the stability of the baseline results in various subsamples. In columns 1 to 3, we redo the analysis of the baseline regression for smaller subsamples. We rank banks according to size and divide them into three equally large samples. Column 1 reports the results for the small banks subsample (first tertile), column 2 contains the medium-sized banks (second tertile), while large banks (third tertile) constitute the sample in the third column. In column 4, we extend the sample and include fast-growing banks and specialized banks (banks with a share of non-interest income larger than 90%). In column 5, we show results when implementing FGLS (Hanushek, 1974). This method allows for correcting for heteroscedasticity induced by using estimated dependent variables. In the regression of the sixth column, the dependent variable provides an indication of extreme systematic risk, i.e. the tail beta of bank stock returns with respect to the returns on a broad European market index (over a period of six year). The tail-beta is a probability and hence bound between [0,1]. Therefore, we employ a generalized linear model, estimated using quasi-maximum likelihood. The independent variables are averages over a six year interval to match the time interval over which the dependent variable is estimated. We apply robust regression techniques to mitigate the effect of outliers in the dataset. In each regression, we include time dummies as well as country fixed effects. Standard errors take into account groupwise heteroscedasticity.