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The Impact of Revenue Diversity on Banking System Stability

by

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Abstract

The dismantling of legal barriers to the integration of financial services is one of the recent, major developments in the banking industry. This led to an expansion of the variety of financial intermediaries and types of transactions. However, this trend may alter banks' risk-taking incentives and may affect overall banking sector stability. This paper analyzes how banks' divergent strategies toward specialization and diversification of financial activities affect their ability to shelter from adverse economic conditions. To this end, market-based measures of banks' extreme systematic risk are generated, using techniques developed for extreme value analysis. Extreme systematic risk captures the probability of a sharp decline in a bank's stock price conditional on a crash in a market index. Subsequently, the impact of (the correlation between) interest and non-interest income (and its components) on this risk measure is assessed. The estimation results reveal that the heterogeneity in extreme bank risk can partially be attributed to differences in banks' reliance on non-traditional banking activities. All non-interest generating activities increase banks' sensitivity to the market index during times of extreme equity market movements. In addition, smaller banks and well-capitalized banks are better able to withstand large adverse economic conditions. Furthermore, the effects are stronger during times of market turbulence compared to a situation of normal economic conditions. Overall, diversifying financial activities in one umbrella institution does not lead to a reduction of extreme banking risk, which may explain why financial conglomerates trade at a discount.

Keywords: diversification, banking, financial stability, extreme value analysis, tail risk.

JEL: G12, G21, G28.

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1 Introduction

In the last thirty years, financial systems in the world have undergone considerable changes. One of the major developments in recent years 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 deregulatory 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 that banks engaged in.

Most of the existing research addressing the issue of the optimal scope of financial corporations takes an industrial organization approach (in accordance with the literature on non-financial corporations) and analyzes whether financial conglomerates create or destroy value (see e.g. Laeven and Levine, 2007; Schmid and Walter, 2007). However, while diversification of activities may create an enormous impact on firms' valuations, for instance in terms of transaction costs or access to capital; for financial corporations the risk aspect is at least as important (if not more). Accordingly researchers started studying whether functional diversification reduces bank risk, by investigating the optimal scope of financial corporations from a portfolio perspective (see e.g. Baele et al., 2007; Stiroh, 2006). We contribute to the empirical literature on the optimal scope of financial corporations by addressing a third perspective, that of financial stability. Prudential supervisors are concerned with extreme bank risk, which may threaten banking system stability. These banking sector supervisors and central banks monitor the entire banking system (of a certain country/region) and can be viewed as holders of a portfolio of banks. Their main interest is in maintaining and protecting the value of their portfolio in times of market stress. 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 banks. However, not all banks need to contribute equally to the risk profile of the supervisor's portfolio and the stability of the banking system. Differences in risk may stem from diversity in the organizational design of banking firms. In this paper, we focus on how divergent strategies toward specialization and diversification of financial activities affect the ability of banks to shelter from adverse economic conditions.

A crucial input in the analysis is our measure of extreme bank risk during adverse economic conditions. We measure banking system stability and the extreme systematic risk profile of listed European banks over different time periods using recently developed techniques (Hartmann et al., 2006 and Straetmans et al., 2008). More precisely, we estimate the probability of crashes in bank stocks, conditional on crashes of a market factor (in casu, a European stock market index). The choice of this measure is determined by two empirical stylized facts on banking panics. First, historically, banking panics occurred when depositors initiated a bank run. Fortunately, true banking panics and associated bank runs by depositors appear to be (almost) history in developed countries (as a result of the development of central banks and deposit insurance schemes). Nevertheless, banks still need to be monitored carefully. In more recent periods, they 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 et al., 2006). Second, Gorton (1988) and Kaminsky and Reinhart (1999) document that most banking panics have been related to macroeconomic fluctuations rather than to prevalent contagion or 'mass hysteria'. Therefore, to capture banking system stability, we measure banks' extreme systematic risk exposures.

Our research contributes to the banking literature in the following fashion. First, by measuring the extreme risk profile for all listed European banks over different time periods we document the presence of substantial cross-sectional heterogeneity and time variation in the co-crash probabilities of European banks. Second, we are able to attribute a substantial degree of this heterogeneity to bank-specific characteristics. More specifically, we contribute to the debate on the optimal functional scope of (financial) firms by analyzing the impact of revenue diversity on banks' extreme risk exposures. Third, 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. While evidence on the relationships between macro-economic conditions, regulatory variables and banking crises is more widespread, this paper may help regulators in understanding why some banks are better able to shelter from the storm.

Our results establish that the shift to non-traditional banking activities, which generate commission, trading and other non-interest income, increases banks' co-crash probabilities and thus reduces banking system stability. Interest income is less risky than all other revenue streams. The estimation results reveal that other indicators of bank specialization in traditional intermediation corroborate the finding that traditional banking activities result in lower extreme systematic risk. Banks with a higher interest margin or higher loans-to-asset ratio are perceived to be less affected by extreme market shocks since higher values of these ratios reduce banks' tail betas. Hence, we can conclude that banks that profitably focus on lending activities are less prone to extreme systematic risk than diversified banks. This questions the usefulness of financial conglomeration as a risk diversification device, at least in times of stock market turmoil. However, we also document that the extent to which shocks to the various income shares are correlated matters for overall and extreme bank risk.

This exclusive focus on the banking sector is warranted. Not only is the banking sector a particularly important sector for the stability of the financial system (due to their interrelatedness with other types of financial intermediaries), banks still occupy a crucial spot in every economy. 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. Hence, preserving banking sector stability is of utmost importance and the priority task of banking supervisors. In addition, the third pillar of the Basel II encourages market participants, rather than regulators, to contribute to the assessment of the overall risk position of the bank. From this perspective, a more complete and coherent disclosure of the different revenue streams may further facilitate a better understanding of the risk exposures of different institutions. Finally, since large banks are more exposed to European-wide shocks, 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 complicates the tasks of national and supranational supervisors. This will be even more the case when banks further increase their cross-border activities. For the locally operating banks, supervision at the country level should suffice to assess the implications of their risk profile.

The following section reviews relevant literature on 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' co-crash probabilities and presents the estimates of banks' tail-β. The subsequent section, Section 5, is divided into three subsections. The first subsection introduces the results for the drivers of heterogeneity in extreme bank risk. In a panel set-up, we relate the co-crash probabilities to different types of financial revenues and other bank-specific control variables. The second subsection 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, delistings or banking crises) that may create a sample selection bias. Subsection 5.3. documents that the information content of the tail beta differs significantly from the information contained in central dependence measures (such as the traditional beta or the correlation between bank stock returns and market returns). Section 6 concludes with policy implications.

2 Revenue diversity and bank risk: selected literature

Most of the theoretical and empirical literature that studies the effects of combining different activities in one umbrella institution focus on the performance aspect. This exclusive 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, 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 extent of correlation between different activities (Dewatripont and Mitchell, 2005) and the organizational structure of the conglomerate (Freixas et al., 2007). Wagner (2007) documents that diversification at financial institutions entails a trade-off. Functional diversification may reduce idiosyncratic risk, but 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. We briefly review the existing empirical evidence on the relationship between revenue diversity and bank risk in normal conditions. Evidence for the US[1] documents that in the nineties 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 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). 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 raising average profits significantly. 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 et al., 2007). Moreover, risk is mainly positively correlated with the share of fee-based activities but not with trading activities (Lepetit et al., 2008). Recent research linking the effect of diversification on 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

[1]Notwithstanding 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.

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 et al. (2004) report that conglomerates exhibit a higher level of risk-taking than non-conglomerates.

However, regulators are especially interested in the frequency and magnitude of extreme events, which threaten the smooth functioning of banks. To the best of our knowledge, only Schoenmaker et al. (2005) take this perspective and analyze the dependence between the downside risk of European banks and insurers. However, their analysis is limited to 10 banks and 10 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.

To sum up, most of the available evidence identifies relationships between functional diversification and bank risk in normal economic conditions. However, it is not so 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 in these circumstances. The remainder of this paper will focus exclusively on this particular aspect.

3 The sample

Since the purpose of the analysis is to investigate how diversity in bank revenue affects European banks' extreme systematic risk, we employ both accounting data and stock price information. We combine information extracted 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. Matching of both datasets is done based on 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, the information from the two datasets is matched using information on some basic accounting data (e.g. total assets, equity,... which are also provided by Datastream). In a similar fashion, we verified the matching of the listed banks.

The analysis is carried out 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 1992-2004. The time span of the sample still 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 6 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. 6 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[2] 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 delisting, IPOs and mergers and acquisitions, our dataset is unbalanced. Some banks are only listed for 6 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 systematic risk exposures over moving windows of 6 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 13 years, we obtain 8 rolling subsamples of 6 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.

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

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 (see e.g. Ferson and Harvey, 1991; Ferson and Korajczyk, 1995; Jagannathan and Wang, 1996; and more recently Santos and Veronesi, 2004). In particular, systematic risk exposures may vary over the business cycle or will be different in normal times versus times of market turbulence. While the combination of correlation-based methods and 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 on 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 et al., 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 to estimate 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 capture 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 the return on a 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 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 systematic risk during crisis periods. Hence, an asset's co-crash probability with the 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). This approach is semi-parametric and allows both for asymptotic dependence and asymptotic independence[3]. Hence, we can avoid making (wrong) distributional assumptions on the asset returns. This approach has recently been used in the finance literature by Poon et al. (2004), Straetmans et al. (2008) and Hartmann et al. (2006).

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 ones 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 empirical counterpart of transforming the stock returns to unit Pareto marginals[4] is based on the following equation:

$$\widetilde{X}_i = \frac{n+1}{n+1-R_{X_i}} \tag{2}$$

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[5]. The only assumption that has to be made is that the minimum series

[3]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.

[4]Other transformations are also feasible. Poon et al. (2004) transform the return series to unit Fréchet marginals.

[5]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.

$Z = \min(\widetilde{X}, \widetilde{Y})$ also exhibits fat tails.

Univariate tail probabilities for fat-tailed random variables can be estimated by using the semi-parametric probability estimator from De Haan et al. (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 selecting m in a region where $\widehat{\alpha}$ is stable (this procedure is usually referred to as the Hill plot method). Next to 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 et al., 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 et al., 2001). Huisman et al. (2001) employ the observations 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, which 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 bank's extreme risk sensitivity.

Measuring extreme systematic 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 of the market risk factor. The market risk factor is captured by a broad European stock market index. For each bank stock (as well as the market factor), 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 co-crash probabilities, 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 a certain probability p. The lower the probability, the more extreme are the situations we consider. We set the crash probability level p at 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 ($= (250 \cdot p)^{-1}$). 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.

Table 1 consists of three panels. Panel A contains information on the extreme losses of the European market index for eight (overlapping) time periods of 6 years. The first block of six years covers the period 1992-1997, the last period runs from 1999 to 2004. 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 -4.6% and -6.9%. It is the 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 -6.5% to -5%. However, the (minimal) severity of a crash, which is expect to occur once every ten year, increases again from 2001 onwards to reach -6.9% in 1998-2003. The periods 1997-2002 and 1998-2003 are the periods with the largest extreme market risk in the sample. Note that in all but one period, 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 6 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. Again, we report the results in eight columns, one for each moving time frame of 6 years over the period 1992-2004. The median crash magnitude of the bank stocks exhibits a similar time pattern as the VaR of the European stock market 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 11.7% for half of the banks in the sample. In five of the eight 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 higher 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. 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 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 European 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 almost twice the VaR of the European index. When looking at the percentiles over the different time periods, we observe that, in almost all time periods, 90% of the banks may fear a larger drop (expected shortfall) in its stock price than the equally unlikely crash (expected shortfall) in the stock market. In the remainder of the paper, we investigate the properties and drivers of co-crash probabilities between bank stock returns and market 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.

Table 2 contains information on the estimated tail-β or co-crash probabilities. The table is structured in a similar fashion as panel B of Table 1. The different columns report values for various moving windows of 6 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 1999-2004. The different lines in Table 2 provide an indication of the cross-sectional dispersion in the extreme systematic 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 9.02% probability that a European bank's stock price will crash, given that the market as a whole crashes. To put it differently, given that there is a large downturn in the market index, on average one out of 11 banks will experience an equally unlikely extreme stock price decline on that day. Recall that the level of the crashes need not be the same for the bank stock return and the conditioning asset (the European index). We rather look at crashes that have a similar probability of occurrence (set at 0.04%). In order to get some intuition in 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 index of 4.6%, there is a 9% probability that the European banks will be confronted with an average fall in their share price of 11.6%.

The first and last column reveal that extreme systematic risk is quite similar in both subsamples. Both the distribution and the level of the tail-βs are roughly the same in the periods 1992-1997 and 1999-2004, with mean tail-βs around 9%. Nevertheless, in the intermediate periods, the dispersion and the level fluctuate largely. The mean tail-β almost doubles in the second subperiod. In three of the 8 subperiods, the co-crash probability exceeds 16%. Moreover, Table 1 shows that in these three periods, the unconditional VaR was also higher. Hence, not only is the co-crash probability larger, the magnitude of the crash would be more severe as well. In the other periods, the mean value of banks' extreme systematic 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 always larger than 13%. 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 shocks. In fact, in each period, some banks have a tail-β (with respect to a broad European index) below 0.04%, which is the unconditional crash probability. This means that these bank stocks crash independently of the stock market. 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 co-crash probabilities.

The estimated co-crash probabilities 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 very 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. 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 co-crash probabilities. In the remainder of the paper, we relate co-crash probabilities to bank-specific characteristics. We fix p at 0.04%. Nevertheless, we also experimented with probabilities in the range of $[0.0001, 0.04]$, resulting in events that happen as infrequently as once every 40 years to yearly events. All reported results with respect to the determinants of tail risk are similar.

5 The impact of revenue diversification on 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 conditional crash probabilities are analyzed by relating the latter 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),

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

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[6]. 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[7] 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[8] in a given period or at the country level. Furthermore,

[6]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.

[7]We employ an iteratively reweighted least squares method. In the initial iterations, Huber (1981) weights are used. In a second set of iterations biweights are employed. This combination of weighting schemes optimally combines the merits of both methods. They are: dealing with extreme outliers and fast convergence.

[8]We could also interact the time and country dummy to absorbs the entire impact of variables that equally affect all banks in a country in a given period. These variables could be: 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 1992-2004. 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

the pooling of cross-sectional and time-series data induces 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[9]. Finally, for many banks, we obtain observations for several, but not all, subperiods, which 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, managing mutual funds and so on. Unfortunately, detailed data on banks' exposure to each of the aforementioned activities is in general not available. However, 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' extreme systematic risk exposures. 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 the basis for analysts and investors to assess the long-term performance potential and risk profile of a bank.

The baseline regression is specified as follows:

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

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).

[9]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 (2008), 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 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 quite important.

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

Next to investigating the impact of revenue diversity, we also include a number of other bank-specific characteristics, $\widetilde{X}$. Summary statistics on the accounting variables are reported in Table 3. The control variables capture strategic choices made by bank managers that may affect a bank's risk profile. The capital buffer measure is included to incorporate the possibility that better capitalized institutions may be less susceptible to market-wide events. We also take into account differences in bank efficiency by including the cost-to-income ratio. 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 prone to market-wide events. Bank profitability is included to control for the 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 important, with the measures of functional diversification. Therefore, we orthogonalize them with respect to all other variables to derive the pure effects that size and profits have[10]. As a result, the coefficients on the other variables capture the full effect on banks' tail-β.

The next subsection introduces the estimation results of the general specification. In the subsequent subsection, we verify the appropriateness of the baseline equation (and its implications) from a method-

[10]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 (as a result of strategic choice) and a historical size component, the residual.

ological and an economic point of view. In the last subsection, we explore how the information content of tail-betas differs from that of central dependence measures.

5.1 The relationship between revenue diversity and banking system stability

The results[11] shown in column 1 of Table 4 reflect the relationships between various bank-specific variables and banks' tail beta measure. 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 that originating from traditional intermediation activities. Put differently, the co-crash probability or 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. However, the impact of the alternative revenue shares does not differ significantly from one another. The estimation results reveal that other indicators of bank specialization in traditional intermediation corroborate the finding that traditional banking activities result in lower extreme systematic risk. Hence, we can conclude that banks that profitably focus on lending activities are less prone to extreme systematic risk than diversified banks[12].

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 extreme systematic risk exposure. On the other hand, the extent to which the growth rates of the various revenue streams are correlated does play an important role. The coefficients are positive, as portfolio theory predicts. Imperfectly correlated revenue streams should reduce bank risk. For three out of the six correlation measures, the coefficients are highly significant. For two others, the p-value is around 15%. A low correlation between shocks to interest income and commission income reduces banks' tail-β significantly. Furthermore, a low correlation between shocks of any of the non-interest income types also contributes positively to

[11] 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.

[12] 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 be less affected by extreme market shocks 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.

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 between the revenue types.

The control variables also reveal interesting relationships. Size is by far the most significant driver of banks' tail betas. Being large makes you more connected to extreme market movements. Larger banks are exposed to many sectors in many countries and are hence more tied to European-wide shocks. Smaller banks are more tied to crashes in a local stock market index since they are predominantly active in their home country. The capital-to-asset ratio exhibits the expected sign and is significant. A larger capital buffer decreases a bank's exposure to extreme market shocks. 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.

Another variable that may suffer from reverse causality is the equity-to-asset ratio 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 6 year period). Nevertheless, the initial profitability level is also significantly and positively related to a bank's extreme risk exposure. Finally, a bank's initial capital ratio significantly reduces banks' exposure to extreme systematic risk. The tail betas of financially strong banks (at the beginning of the period) are less affected by a crash in the stock market return index.

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:

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

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 all exceed 0.20. The effect is the 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 $2.4-3.6$ 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 3.6 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 commission 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 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 their extreme risk exposure. An increase of the equity-to-assets ratio of 0.05 will result, all else equal, in a drop in the tail beta of almost 4.5 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 occurring if there is a large, negative shock to the European market return index. This increase equals a substantial proportion of the average tail-β. Depending on the time period, an increase with 5 basis points corresponds to 30% of the average tail-β in 1994-1999 and more than 50% of the average tail-β in 1999-2004.

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. That is, 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). On the other hand, we are able to assess the impact of a change in X_i for banks that only differ with respect to another variable X_j. The three panels of Figure 1 provide an indication of the former. The top panel represents the marginal effect of a change in the share of commission income over the range of observed values of that variable, while fixing the other independent variables at their sample mean. The values on the X-axis represent the share of commission income, while the values at the Y-axis indicate the marginal effect (as obtained from Equation (9)). The middle panel provides a similar graph for the share of trading income and the lower panel contains information on the other operating income share. Column 2 of Table 4 shows the marginal impact of the non-traditional banking activities when they are evaluated at the sample mean. From Figure 1, we learn, however, that the implied effects differ substantively when they are assessed at other values. The marginal effect of a change in one variable increases monotonously with the value of that variable. But the slope differs across the revenue shares. The impact of trading 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 commission income share on banks' co-crash probabilities is 0.267 at the sample mean (which is 26% of total income). The impact is only half as large, around 0.12, if an otherwise equal bank only derives a small proportion (5.5%) of its income from commission generating activities. On the other hand, a bank with an even greater reliance on commission income, 41% of total operating income, will have a marginal effect of 0.37, which is three times larger than the bank in the latter case.

The six panels of Figure 2 show differences in the marginal effects of the three alternative revenue types for banks that additionally differ in another aspect. The left hand side plots reveal information on how differences in the degree of capitalization affect these marginal effects, while the right hand side panels contain similar information for large versus small banks. Again, the top, middle and bottom rows represent respectively the marginal effects of changes in commission income, trading income and other operating income. In each plot, the solid line represents the mean bank, with the exception that either the capital ratio or bank size is fixed at the 75^{th} percentile. The dotted line shows the banks that exhibit the 25^{th} percentile of that ratio. Consider for example the top left box. This represents the marginal effects associated with changes in commission income at various levels of the commission income share for high and low capitalized banks. Consider again the benchmark values of the average bank (as reported in column 2 of Table 4). At the mean commission income share, the marginal effect is 0.267. Since a larger capital buffer reduces banks' co-crash probabilities with the market, the impact will be larger for less capitalized banks. The differential impact between the low and high capital ratio banks is 0.078

($= 0.326 - 0.247$) at the sample mean of commission income. This impact gap widens for banks that are more heavily involved in commission and fee-generating activities and is for instance 0.102 when the commission income share is 40%. Put differently, in order to experience similar marginal effects of an increase in commission 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. Similar explanations can be made for the other revenue types. At low values of trading income and other operating income, the differential impact is already quite large. The right hand side boxes confirm that 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 Support for the baseline equation

Many banks are not included in all subperiods. Hence, the panel data set is unbalanced. If (non-)selection in the sample occurs randomly, then the results of the baseline regression are not subject to a selection bias. Some sources of (dis)appearing in (from) the sample are potentially non-random and may affect the estimated relationships. Examples of non-random events that may bias the estimates are IPOs, delistings, M&As, or the elimination of infrequently traded bank stocks from the sample. In this subsection, we describe the analysis of this events. The estimation results are documented in Table 5.

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 1992-2004. In column 1 of Table 5, we present the results when all observations on such banks are discarded[13]. The sample size reduces to 618 observations. However, none of the results reported in Table 4 alters. The conclusions regarding the magnitude and significance of the impact of revenue shares and the correlation of their growth rates are still valid.

Another important source of unbalancedness are mergers and acquisitions. We check the stability

[13] 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.

of the results by leaving out the banks that are involved in an M&A. Column 2 of Table 5 contains the estimation results when both pre-M&A entities and post-M&A entities are excluded from the sample. The results hardly change. If anything, the coefficients on the alternative revenue streams as well as the correlation coefficients become larger, which only strengthens the findings of the baseline.

We also examine the aforementioned selection issues simultaneously. Column 3 contains the results for a substantially reduced sample (as a result of dropping banks that are involved in one or more of the selection criteria). In column 4, 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. 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. Furthermore, banks that enter the sample after an IPO or drop due to a delisting have, as expected, a higher extreme systematic risk exposure. To conclude, although the panel dataset is unbalanced, the sources of the missing values in the dataset do not affect the relationships of interest.

Some European countries have been confronted with a banking crisis[14] 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 5 of Table 5, 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 5 show that including the crisis periods does not affect the results. 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 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

[14]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.

correlation. Column 6 of Table 5 reports the results when we do include the fast growing banks. In the last column of Table 5, we report the results for the full sample of commercial banks and bank holding companies. In this case, the sample size increases by 10% to 743 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, but 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).

5.3 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 of the market risk factor. 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 systematic 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 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 systematic risk exposures over moving windows of 6 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. Next to calculating a bank's market beta, we also compute the squared correlation coefficient with the market returns. 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 (or correlation coefficient) is very high. Across the eight time windows of six years, it fluctuates in the range of 60% to 75%. Hence, banks with a large exposure to market movements in normal economic conditions will be strongly tied to extreme movements as well. The high correlation implies that both dependence measures share an important component. Second, we established significant relationships between non-traditional banking activities and banks' extreme systematic risk exposures (see Column 1 of Table 4 and 6). We run similar regressions, but substitute the dependent variable. The results are reported in Columns 2 of Table 6. The tail beta is replaced as dependent variable by the squared correlation coefficient. We discover similar relationships. All non-interest generating activities increase the exposure of banks' stock returns to market movements. However, where the impact of the three non-interest generating activities on the tail beta is significantly different from zero, this is not the case for the share of operating income in normal conditions. Moreover, the impact of trading income is significantly larger than the impact of commission income and other operating income. Contrary to expectations, banks systematic risk will be higher the more equal the shares of interest and non-interest income are. The coefficient on HHI_{REV} is negative and significant. Only for the two Herfindahl Hirschmann indices do we observe different signs in Columns 1 and 2 (or 3). The six measures of the correlation between shocks to pairs of income shares are all positively related to the squared correlation coefficient of a bank's stock return and the returns on a market index. Four 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 squared correlation coefficient to the baseline regression (Column 3 of Table 6). 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[15] 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 a bank's extreme risk profile. However, only the share of commission and fee 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 increases banks' tail-β. Measures of bank size and bank profitability are significant

[15]From Column 2 of Table 6, 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 6. Therefore, we focus more on the magnitude of the coefficient rather than the significance level.

and hence enforce the positive indirect effect. Fourth, in column 4 Table 6, we report a joint effect[16], which is the sum of the direct (coefficients in Column 3) and indirect effect (coefficient on the central dependence measure times 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 or other operating income on a bank's extreme risk profile is larger than the indirect effect. Concerning trading income, the direct effect is only one third as large as the overall effect. The impact of correlated shocks between interest income and any of the non-interest income activities works predominantly via the general, central risk measure. However, the opposite observation can be made for the correlation between pairs of non-interest generating activities.

To conclude, we discover a high correlation between banks' systematic risk exposures in normal and stress periods. Furthermore, the shift to non-traditional banking activities has increased banks' systematic risk 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.

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 many resources in analyzing and safeguarding banking sector stability. Reliable indicators of banking system stability are of 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 extreme systematic risk measure captures the probability of a sharp decline in a bank's stock price conditional on a crash in a market 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. However, some banks remain specialized in traditional intermediation activities or target local customers.

When relating the co-crash probabilities 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-

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

traditional banking activities increases banks' co-crash probabilities and thus reduces banking system stability. Interest income is less risky than all other revenue streams. However, the impact of the alternative revenue shares (commission and fee income, trading income, other operating income) does not 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 are less prone to extreme systematic risk 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 extreme systematic risk. Furthermore, bank size is by far the most significant driver of banks' tail betas. Larger banks are exposed to many sectors in many countries and are hence more tied to European wide shocks. A larger capital buffer decreases a bank's exposure to extreme market shocks. This finding is expected and underlines the importance of capital adequacy as a signal of bank creditworthiness.

The established relationships bear implications for bank supervision. Since the large banks are more exposed to European-wide 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. 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 the Basel II. Market participants, rather than armies of regulators, will do some of the work in assessing the overall risk position of the bank. A more complete and coherent disclosure of the different revenue streams facilitates a better understanding of the risks being taken by different institutions. 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 components, especially with respect to commission and fee income. The US reporting requirements, which include a 12-item distinction of non-interest income (since March 2001) may be a useful benchmark.

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Table 1: Unconditional Value at Risk and Expected Shortfall

Panel A: returns on European stock market index								
	1992-1997	1993-1998	1994-1999	1995-2000	1996-2001	1997-2002	1998-2003	1999-2004
Observed minimum return	-0.043	-0.045	-0.045	-0.045	-0.059	-0.059	-0.059	-0.059
VaR(EU-index) with p=0.04%	-0.046	-0.065	-0.060	-0.050	-0.055	-0.068	-0.069	-0.065
ES (EU-index) with p=0.04%	-0.073	-0.110	-0.094	-0.068	-0.075	-0.093	-0.094	-0.090

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
5th percentile	-0.236	-0.273	-0.243	-0.175	-0.178	-0.162	-0.169	-0.171
10th percentile	-0.186	-0.210	-0.179	-0.150	-0.161	-0.157	-0.155	-0.152
25th percentile	-0.124	-0.145	-0.139	-0.128	-0.130	-0.137	-0.139	-0.125
50th percentile	-0.090	-0.117	-0.110	-0.108	-0.113	-0.116	-0.112	-0.100
75th percentile	-0.078	-0.091	-0.091	-0.083	-0.085	-0.086	-0.086	-0.071
90th percentile	-0.054	-0.074	-0.066	-0.063	-0.062	-0.070	-0.064	-0.056
95th percentile	-0.051	-0.058	-0.054	-0.055	-0.051	-0.053	-0.059	-0.049
mean	-0.116	-0.136	-0.123	-0.109	-0.117	-0.113	-0.113	-0.104
standard deviation	0.080	0.103	0.080	0.042	0.075	0.035	0.038	0.040
number of obs.	85	97	96	91	88	95	95	100

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
5th percentile	-0.358	-0.403	-0.362	-0.262	-0.266	-0.244	-0.251	-0.254
10th percentile	-0.302	-0.318	-0.284	-0.233	-0.233	-0.225	-0.230	-0.230
25th percentile	-0.196	-0.220	-0.207	-0.190	-0.194	-0.197	-0.202	-0.186
50th percentile	-0.144	-0.174	-0.161	-0.152	-0.161	-0.163	-0.158	-0.139
75th percentile	-0.110	-0.134	-0.129	-0.120	-0.120	-0.115	-0.118	-0.110
90th percentile	-0.087	-0.107	-0.098	-0.086	-0.086	-0.092	-0.091	-0.079
95th percentile	-0.069	-0.088	-0.080	-0.063	-0.077	-0.085	-0.077	-0.062
mean	-0.174	-0.203	-0.183	-0.160	-0.168	-0.161	-0.161	-0.151
standard deviation	0.111	0.134	0.108	0.067	0.099	0.056	0.056	0.060
number of obs.	85	97	96	91	88	95	95	100

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 stock market 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 betas

Co-crash probabilities (tail-beta) of European bank stock returns w.r.t. a European stock market index								
	1992-1997	1993-1998	1994-1999	1995-2000	1996-2001	1997-2002	1998-2003	1999-2004
5th percentile	0.04	0.08	0.04	0.05	0.21	0.13	0.10	0.05
10th percentile	0.07	0.16	0.26	0.20	0.37	0.34	0.36	0.13
25th percentile	0.52	1.75	1.38	2.00	2.95	2.09	1.32	0.49
50th percentile	3.56	9.19	10.69	10.49	11.42	8.67	6.21	3.31
75th percentile	13.21	27.01	24.59	20.31	25.55	20.61	19.03	14.64
90th percentile	22.46	42.59	41.99	30.21	44.02	29.98	26.58	25.73
95th percentile	32.13	54.72	54.79	47.74	49.41	35.03	30.51	37.94
mean	9.02	16.54	16.61	14.08	16.84	12.76	11.03	9.80
standard deviation	14.06	18.22	18.35	15.37	17.03	12.60	12.07	14.06
number of obs.	86	97	97	91	88	95	95	103

Note: this table contains information on the tail-betas or co-crash probabilities for the set of listed European banks. 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	0.591	0.173	0.190	0.543	0.635	0.698	0.785
Commission and Fee income	0.274	0.146	0.125	0.192	0.255	0.310	0.600
Trading Income	0.062	0.069	0.000	0.017	0.049	0.085	0.189
Other Operating Income	0.064	0.100	0.000	0.001	0.035	0.078	0.239
Diversification of non-interest income (HHI-NON)	0.618	0.162	0.388	0.500	0.585	0.730	0.915
Diversification of interest vs non-interest income (HHI-REV)	0.577	0.081	0.501	0.518	0.555	0.602	0.739
Correlation (interest income growth,commission income growth)	0.178	0.561	-0.767	-0.308	0.269	0.701	0.921
Correlation (interest income growth,trading income growth)	0.011	0.473	-0.782	-0.373	0.007	0.376	0.797
Correlation (interest income growth,other operating income growth)	0.034	0.462	-0.688	-0.334	-0.001	0.408	0.779
Correlation (commission income growth,trading income growth)	0.111	0.467	-0.661	-0.243	0.106	0.471	0.866
Correlation (commission income growth, other operating income growth)	0.093	0.483	-0.730	-0.280	0.106	0.479	0.842
Correlation (trading income growth, other operating income growth)	0.054	0.464	-0.734	-0.302	0.050	0.402	0.812
log Total Assets	9.442	2.106	6.297	7.745	9.284	11.029	12.961
Equity-to-Assets	0.077	0.073	0.030	0.047	0.058	0.080	0.160
Cost-to-Income	0.652	0.124	0.439	0.585	0.650	0.722	0.852
Loans-to-Assets	0.533	0.164	0.206	0.455	0.546	0.633	0.794
Return on Equity	0.122	0.103	0.007	0.080	0.129	0.171	0.237

Note: this table contains information on the bank-specific variables used in this paper. The ratios are first computed as averages over each 6 year period. The first set of rows contains the variables of interest, namely the revenue measures. 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 five rows provide summary statistics on the control 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 betas

	Baseline regression	Marginal effects at sample mean	Baseline regression (all ratios measured as intial values
Constant	-4.3642***		-4.4395***
	[0.5598]		[0.5270]
Commission and Fee income	3.3817***	0.267	3.6200***
	[0.5154]		[0.6716]
Trading Income	4.1497***	0.328	3.1769***
	[0.7026]		[0.5870]
Other Operating Income	2.6638**	0.210	1.8914**
	[1.0797]		[0.9365]
HHI (Non Interest Income)	-0.4296	-0.034	-0.3603
	[0.3179]		[0.4710]
HHI (Revenue)	0.0748	0.006	-1.2090*
	[0.9083]		[0.6841]
Corr (Δln(II), Δln(CI))	0.2575***	0.020	0.1854*
	[0.0857]		[0.1109]
Corr (Δln(II), Δln(TI))	0.0811	0.006	0.1107
	[0.1688]		[0.1694]
Corr (Δln(II), Δln(OI))	0.1355	0.011	0.0937
	[0.0944]		[0.0827]
Corr (Δln(CI), Δln(TI))	0.1602	0.013	0.1267
	[0.1133]		[0.1082]
Corr (Δln(CI), Δln(OI))	0.2690***	0.021	0.1566**
	[0.0792]		[0.0792]
Corr (Δln(TI), Δln(OI))	0.1865**	0.015	0.1717**
	[0.0804]		[0.0777]
Size	0.5518***	0.044	0.5303***
	[0.0477]		[0.0453]
Equity-to-Assets	-11.2676***	-0.890	-7.7508***
	[1.7736]		[1.9419]
Cost-to-Income	-1.6562**	-0.131	-0.9339*
	[0.7012]		[0.5048]
Return on Equity	2.0357***	0.161	0.4020***
	[0.7209]		[0.1373]
Observations	681		669
Number of bankid	134		132
R-squared	0.770		0.748
AIC	0.598		0.608
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 extreme systematic risk over a period of six year. The co-crash probability is 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 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.

Table 5: Support for the baseline equation

	Exclude banks that have been involved in an IPO, Delisting or which share is illiquid	Exclude pre-M&A and post M&A entities from sample	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 sample + fast-growing banks	Baseline sample + fast-growing banks + Specialized banks
Constant	-4.5957***	-3.7628***	-4.2023***	-4.3620***	-3.9051***	-4.0434***	-4.5259***
	[0.5540]	[0.6164]	[0.7133]	[0.6113]	[0.5375]	[0.5312]	[0.4366]
Commission and Fee income	3.1945***	3.8771***	3.6175***	3.3257***	3.1769***	2.9036***	2.9985***
	[0.6159]	[0.5781]	[0.6998]	[0.4462]	[0.4582]	[0.4197]	[0.3797]
Trading Income	4.2481***	5.2714**	5.9675*	4.5108***	3.7903***	3.3564***	3.2408***
	[0.6987]	[2.2367]	[3.0915]	[0.8009]	[0.7279]	[0.5236]	[0.5107]
Other Operating Income	2.5143**	3.5605***	4.3430***	2.8996***	2.7506**	2.1745***	3.2748***
	[1.0708]	[1.0237]	[1.1809]	[0.8982]	[1.1251]	[0.8393]	[0.7707]
HHI (Non Interest Income)	-0.4972	0.1782	0.1184	-0.2963	-0.7654	-0.6237**	-1.5364***
	[0.3648]	[0.6809]	[0.6193]	[0.2939]	[0.5226]	[0.2878]	[0.3035]
HHI (Revenue)	0.017	-0.1287	0.0389	0.1546	-0.6308	-0.0254	0.5044
	[0.9311]	[0.7599]	[0.7327]	[0.6989]	[1.1538]	[0.7963]	[0.7807]
Corr (Δln(II), Δln(CI))	0.2611***	0.3891***	0.3897***	0.3119***	0.2402**	0.2060**	0.3301***
	[0.0766]	[0.1367]	[0.1165]	[0.0609]	[0.1093]	[0.0816]	[0.0935]
Corr (Δln(II), Δln(TI))	0.0666	0.0318	-0.0346	0.0268	0.0553	0.048	-0.0154
	[0.1786]	[0.1607]	[0.1549]	[0.1499]	[0.2122]	[0.1575]	[0.1934]
Corr (Δln(II), Δln(OI))	0.1364	0.1465	0.1392	0.1397	0.1657	0.1218	-0.0398
	[0.0904]	[0.1394]	[0.1563]	[0.0990]	[0.1116]	[0.0753]	[0.0776]
Corr (Δln(CI), Δln(TI))	0.2108**	0.0904	0.1746	0.2241**	0.2325	0.121	0.1879*
	[0.1075]	[0.1503]	[0.1446]	[0.1055]	[0.1439]	[0.1073]	[0.1056]
Corr (Δln(CI), Δln(OI))	0.1692***	0.2926**	0.1945**	0.2527***	0.1908**	0.2071***	0.1808***
	[0.0619]	[0.1246]	[0.0924]	[0.0720]	[0.0761]	[0.0674]	[0.0683]
Corr (Δln(TI), Δln(OI))	0.1976**	0.3183**	0.3284**	0.1849*	0.1648*	0.2207***	0.1369*
	[0.0866]	[0.1302]	[0.1329]	[0.1023]	[0.0917]	[0.0808]	[0.0808]
Size	0.5680***	0.6165***	0.6348***	0.5917***	0.5344***	0.5331***	0.5170***
	[0.0437]	[0.0719]	[0.0761]	[0.0398]	[0.0510]	[0.0478]	[0.0415]
Equity-to-Assets	-11.1314***	-13.0663***	-12.1957***	-11.1697***	-8.5329***	-10.8882***	-3.2572**
	[1.9584]	[2.1221]	[2.5271]	[1.6022]	[2.4998]	[1.5156]	[1.5628]
Cost-to-Income	-1.0162	-3.1516***	-2.4917***	-1.7583***	-1.4927*	-1.4858**	-1.1372**
	[0.7044]	[0.5547]	[0.5976]	[0.5835]	[0.9061]	[0.5872]	[0.5290]
Return on Equity	2.4543***	2.4951***	3.2358***	2.4909***	3.3424***	1.8745***	1.6398***
	[0.8086]	[0.7095]	[0.8285]	[0.8547]	[0.6042]	[0.6622]	[0.6341]
Observations	618	540	483	681	552	729	743
Number of bankid	110	95	74	134	121	140	143
R-squared	0.774	0.788	0.794	0.779	0.773	0.772	0.762
AIC	0.605	0.580	0.586	0.609	0.631	0.588	0.585
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 eliminate the banks whose shares have been illiquid in previous sample periods, banks that go public and banks that are delisted. In Column 2, we check whether M&As that occurred during the sample period affect the results. We estimate the baseline regressions respectively without the banks that constitute the separate entities before the M&A and without the resulting new entity after the M&A. In column 3, we redo the analysis and include only those banks that were not involved in one of the aforementioned events. In column 4, we use the baseline sample but include (not reported) dummies for each of the aforementioned events. In Column 5, we exclude a bank-time observation if the banking industry in the associated country experienced a banking crisis in one of the 6 years of that timeframe. In the last two columns, we extend the sample and include respectively fast-growing banks and specialized banks (banks with a share of non-interest income larger than 90%). In the regressions, the dependent variable, the tail-β, provides an indication of extreme systematic risk over a period of six year. The co-crash probability is 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.

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Table 6: the information content of tail betas versus traditional betas

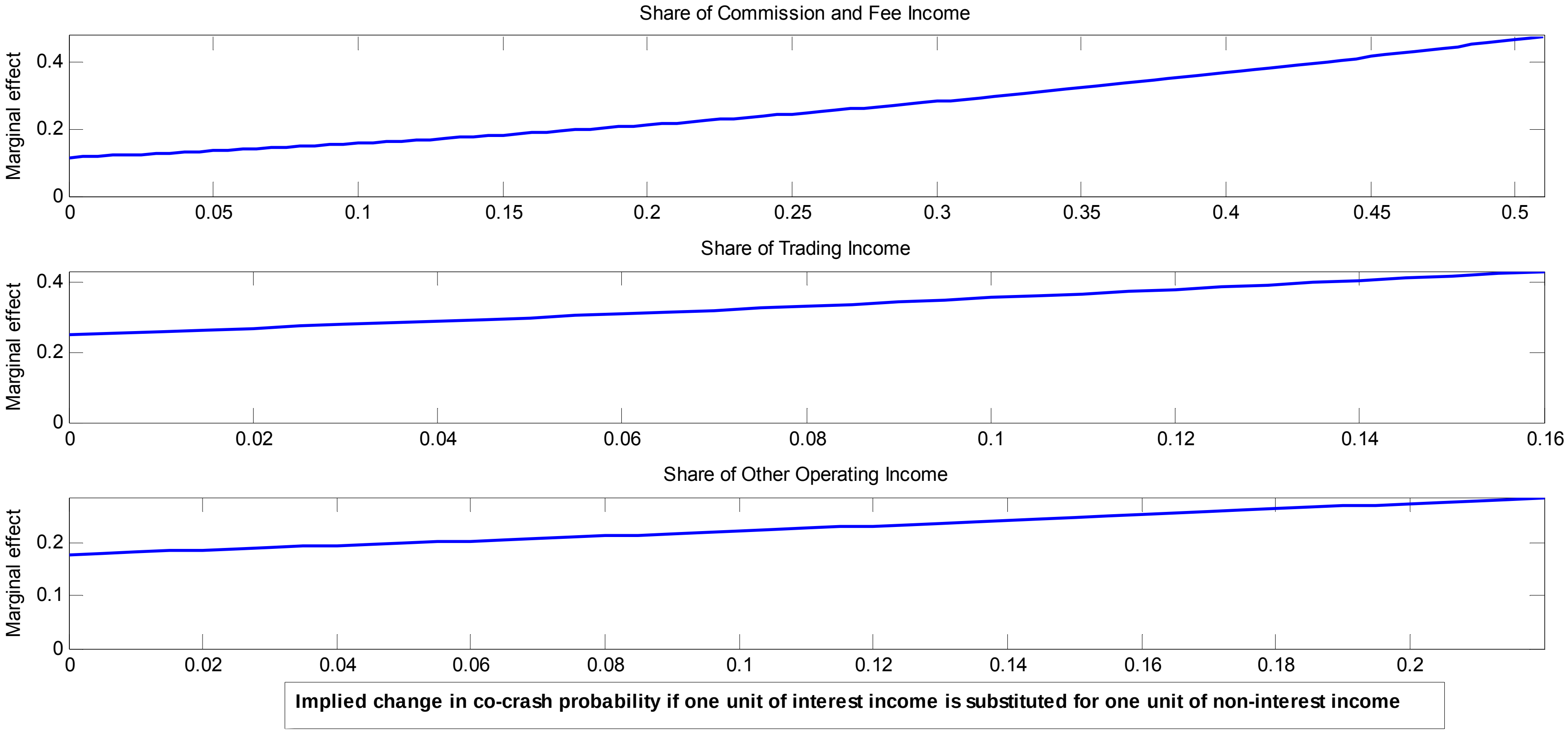
	Baseline	Determinants of squared correlation coefficient	Baseline with squared correlation coefficient as additional regressor	Joint Effects
Constant	-4.3642***	0.2902***	-5.4243***	
	[0.5598]	[0.0940]	[0.5832]	
Commission and Fee income	3.3817***	0.2190**	2.3323***	3.055
	[0.5154]	[0.1060]	[0.5113]	
Trading Income	4.1497***	0.7331***	1.2593	3.678
	[0.7026]	[0.1127]	[0.9139]	
Other Operating Income	2.6638**	0.1688	1.2652	1.822
	[1.0797]	[0.1261]	[1.0381]	
HHI (Non Interest Income)	-0.4296	0.0614	-0.7118**	-0.509
	[0.3179]	[0.0379]	[0.3185]	
HHI (Revenue)	0.0748	-0.3617***	1.3752*	0.182
	[0.9083]	[0.1181]	[0.8209]	
Corr (Δln(II), Δln(CI))	0.2575***	0.0670***	0.008	0.229
	[0.0857]	[0.0121]	[0.0860]	
Corr (Δln(II), Δln(TI))	0.0811	0.0128*	0.0342	0.076
	[0.1688]	[0.0072]	[0.1584]	
Corr (Δln(II), Δln(OI))	0.1355	0.0311***	0.0028	0.105
	[0.0944]	[0.0097]	[0.1023]	
Corr (Δln(CI), Δln(TI))	0.1602	0.0188	0.0649	0.127
	[0.1133]	[0.0121]	[0.1235]	
Corr (Δln(CI), Δln(OI))	0.2690***	0.0143	0.1875**	0.235
	[0.0792]	[0.0108]	[0.0849]	
Corr (Δln(TI), Δln(OI))	0.1865**	0.0180*	0.1582**	0.218
	[0.0804]	[0.0104]	[0.0801]	
Size	0.5518***	0.0656***	0.2963***	0.513
	[0.0477]	[0.0069]	[0.0712]	
Equity-to-Assets	-11.2676***	-0.9070***	-8.1910***	-11.183
	[1.7736]	[0.2339]	[1.8075]	
Cost-to-Income	-1.6562**	-0.1432*	-1.018	-1.490
	[0.7012]	[0.0754]	[0.7553]	
Return on Equity	2.0357***	0.1992**	1.0565	1.714
	[0.7209]	[0.0864]	[0.8501]	
Squared correlation coefficient			3.2990***	
			[0.5947]	
Observations	681	681	681	
Number of bankid	134	134	134	
R-squared	0.770	0.885	0.790	
AIC	0.598	-2.314	0.595	

Standard errors in brackets (clustered at country level)

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

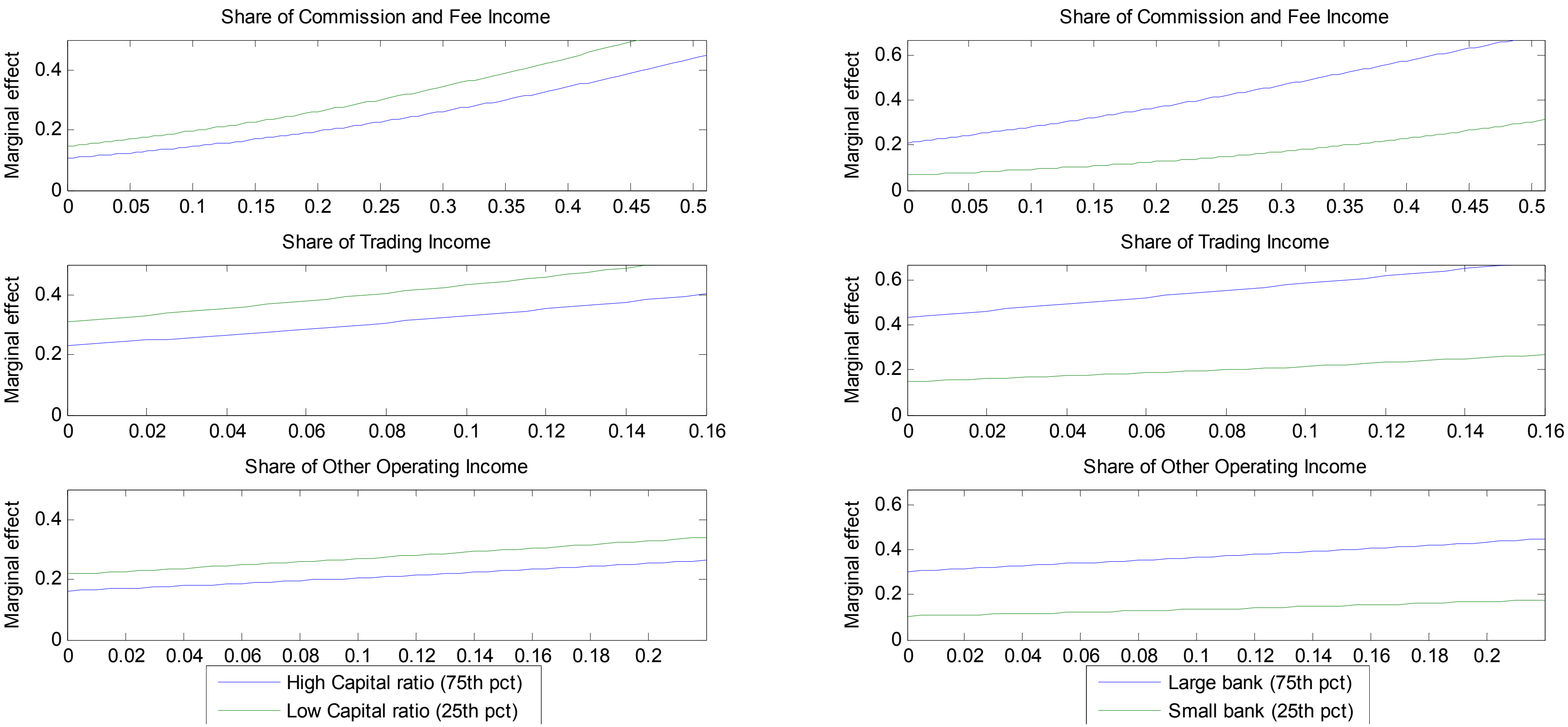
Note: The table presents information on the differential impact of various bank characteristics on the tail beta and more traditional measures that capture dependency in normal times. The first column reports the results for the baseline regression. In this regression, the dependent variable, the tail-β, provides an indication of extreme systematic risk over a period of six year. The co-crash probability is 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 the squared correlation coefficient is used to measure the normal dependence between bank stock returns and the returns on a European index. Column 2 reports the results for the drivers of the squared correlation coefficient. In column 3, this squared correlation coefficient 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 and an indirect effect via the traditional dependence measure.

Chart 1: Marginal effect on the co-crash probability of an increase in a non-interest income share



Note: This chart presents information on the marginal impact of a change in the share of a non-interest revenue source. The top panel represents the marginal effect of a change in the share of commission income over the range of observed values of that variable, while fixing the other independent variables at their sample mean. The values on the X-axis represent the share of commission income, while the values at the Y-axis indicate the marginal effect. The middle panel provides a similar graph for the share of trading income and the lower panel contains information on the other operating income share. The marginal effects should be interpreted as the extent to which the co-crash probability will increase if one unit of the share of interest income is transferred to one of the three alternative revenue shares.

Chart 2: Marginal effects depending on the level of capital or size of the bank



Note: This chart presents information on the marginal impact of a change in the share of a non-interest revenue source. Each chart contains plots with the marginal effect of a change in the share of a non-interest income source over the range of observed values of that variable. All but one of the other independent variables are fixed at their sample mean. In addition, one other independent variable is not evaluated at its sample mean. In the left hand side graphs, the equity-to-asset ratio can take on different values, whereas bank size varies in the right hand side graphs. The solid, blue line corresponds to the case where bank capital (bank size) is evaluated at the value corresponding with its 75th percentile (rather than the mean). If bank capital (or bank size) is set at the value of the 25th percentile, the marginal effects are represented by the dotted, green line. The top panel represents the marginal effect of a change in the share of commission income over the range of observed values of that variable. The values on the X-axis represent the share of commission income, while the values at the Y-axis indicate the marginal effect. The middle panel provides a similar graph for the share of trading income and the lower panel contains information on the other operating income share. The marginal effects should be interpreted as the extent to which the co-crash probability will increase if one unit of the share of interest income is transferred to one of the three alternative revenue shares. In each panel, two lines are plotted.