The impact of revenue diversity on banking system stability*

Olivier De Jonghe[†]

Ghent University

February 2007

Abstract

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 non-interest income (and its components) on this risk measure is assessed. 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. 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. 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.

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

JEL: G12, G21, G28.

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 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

*Part of the research was undertaken while Olivier De Jonghe was an intern at the ECB (Directorate Financial Stability) and the NBB (Financial Stability Division). The author would like to thank the members of both departments for helpful comments and discussions.

†De Jonghe is Research Assistant of the Fund for Scientific Research - Flanders (Belgium) (F.W.O.-Vlaanderen). Olivier De Jonghe (olivier.dejonghe@ugent.be), Ghent University, Wilsonplein 5D, 9000 Ghent. Tel: 0032/9264.78.96. Fax: 0032/9264.89.95.

umbrella. Similar deregulatory initiatives took place in the US, by means of the Gramm-Leach-Bliley Act of 1999. The expansion in the variety of intermediaries and financial transactions has enormous benefits, for instance in terms of transaction costs, access to capital or risk sharing. However, the changes have potential downsides especially in terms of excessive risk-taking and the stability of the financial system. This is reflected in financial sector volatility, which has steadily increased over the past three decades and reached extraordinary levels from 1998 to 2002 (Houston and Stiroh, 2006). Much of this recent turbulence can be attributed to a series of major financial shocks. Hence, as a result of financial development, financial institutions may have increased their incentives to take tail risks, which may cause a low probability, but highly costly downturn (Rajan, 2005).

In this paper, we focus on how divergent strategies toward specialization and diversification of financial activities affect banks their ability to shelter from adverse economic conditions. We analyze whether diversified banks contribute more to overall banking sector stability vis-à-vis their specialized counterparts. The 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 are still the heart of every economy. They play a central role in the money creation process and in the payment system. Moreover, by providing loans they contribute to the financing of investment and growth. Disruptions in the smooth functioning of the banking industry tend to exacerbate overall fluctuations in output and banking crises are associated with significant output losses. Hence, preserving banking sector stability is of utmost importance and the priority task of banking supervisors. Central banks and banking sector supervisors 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 continuity of banks. However, not all banks contribute equally to the risk profile of the supervisor's portfolio and the stability of the banking system. Remarkably, little is known about the extent and the sources of heterogeneity in banks' extreme risk profile. To fill this void, we first measure banks' extreme systematic risk exposures using multivariate extreme value analysis. This allows analyzing the time evolution as well as the cross-sectional dispersion in banks' extreme risk profile. Subsequently, we relate this measure to bank-specific accounting data.

More precisely, as measure of banking system stability we estimate the probability of crashes in bank stocks, conditional on crashes of a market factor. This co-crash probability is also labelled the tail-β since it can be seen as the equivalent of the market beta in times of market stress (Straetmans et al., 2007). Hartmann et al. (2006) introduced this measure in the banking literature to compare banking system stability across the Atlantic. They estimate the tail-β for the 25 largest European and US banks and already discover a fair amount of heterogeneity in this set of large banks. The cross-sectional dispersion in banks' tail-β is larger in Europe than in the US. We extend their analysis and measure the extreme risk profile for all listed European banks over different time periods.

This enables discovering substantial cross-sectional heterogeneity and time variation in the co-crash probabilities of European banks. To our knowledge, no evidence exists on the sources of this heterogeneity. We are able to attribute a sufficient degree of this heterogeneity to bank-specific characteristics. We 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. The results are interesting in light of the third pillar of the Basel II. A more complete disclosure of the different revenue streams should allow a better understanding of the risks being taken on by different institutions. This will allow market participants itself, rather than armies of regulators, to do some of the work in assessing the overall risk position of the bank.

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 other two subsections deal 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. 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., 2006).

A number of authors empirically identify the impact of combining different financial activities on a bank's risk profile during normal economic conditions. However, regulators are especially interested in the frequency and magnitude of extreme events, which threaten the smooth functioning of banks. To 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 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.

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, 2004 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. Moreover, risk is mainly positively correlated with the share of fee-based activities but not with trading activities (Lepetit et al., 2006). 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 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.

To sum up, most of the available evidence identifies relationships between functional diversification and bank risk in normal economic conditions. However, it is not as 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.

[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.

3 The sample

Since the purpose of the analysis is to investigate how diversity in bank revenue affects European banks' extreme systematic risk, we need 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 (a scheme 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 is 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 with 15 member states. 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 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. Third, given the focus of our study, the impact of revenue diversity, we consider a wide range of financial intermediaries ranging from commercial banks, savings banks, cooperative banks, mortgage banks, credit institutions to bank holding companies.

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 the entire period. Comparing banks' behavior and risk profile is only sensible if each banks' 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.

4 Banking system stability

4.1 Extreme systematic risk: measurement

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. Hence, systematic risk is the risk of movements in the overall market, which cannot be diversified away. There exists ample evidence that firms' exposure to systematic risk is not constant over time (see e.g. Ferson and Harvey, 1991; Bekaert and Harvey, 1997; Baele, 2005). In particular, systematic risk exposures may vary over the business cycle or will be different in normal times versus times of market turbulence. Given the focus on (banking sector) instability, we are particularly interested in firms' systematic risk exposures when the stock market crashes.

Typically, systematic risk is measured using a firm's beta, which describes the sensitivity of an asset's return to broad market movements. A stock's beta is computed by dividing the covariance between the firm's stock return and the market return by the squared volatility of the market's return. Hence, correlation based methods are used to assess whether comovements change in different states. However, the correlation measure is very much tied to the multivariate normal distribution which focuses on the dependency in the center of the distribution. But the multivariate normal distribution dramatically underestimates the observed probability mass in the tails. Hence, this dependency in the center may be uninformative for what happens in the tails of the distributions. In fact, there exists quite a bit of 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 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 market stress. 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., 2007).

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. 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. (2007) and Hartmann et al. (2006). The joint probability is determined by the dependence between the two assets and their marginal distributions. Since the interest lies in 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[2] is based on the following equation:

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

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

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[3]. The only assumption that has to be made is that the minimum series $Z = \min(\widetilde{X}, \widetilde{Y})$ also exhibits heavy 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 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

[3] 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.

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. Moreover, 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 relation 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 measure 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.

4.2 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 two 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 dropped 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 deciles 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 11.4% for half of the banks in the sample. In the 6^{th} and 7^{th} period under consideration, the median daily VaR was also lower or equal to -11%. The mean VaR is never lower (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 0.05. 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).

The comparison of the estimated VaR of the European index (reported in panel A) and the mean (or median) crash level of the bank stock returns, shows that most bank stocks have a higher downside risk potential than the European index[4]. 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 any time period, 75% of the banks may fear a larger drop in its stock price than the equally unlikely crash in the stock market. In some periods, this is even the case for more than 90% or 95% of the banks.

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 year. 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 7.91% 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 12 or 13 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 almost an 8% probability that the European banks will be confronted with an average fall in their share price of 11.5%.

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 8%. 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 14%. 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

[4] This need not be surprising, since we are comparing losses on a single asset with losses on a broad porfolio.

periods, the mean value of banks' extreme systematic risk approximates 10%. 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 10%. 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.

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 them to bank-specific variables. We are primarily interested in knowing how different financial activities affect banking system stability. More specifically, we will focus our analysis on the differential impact that different revenue sources may have on banks' extreme systematic risk exposures. 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 European banks' revenue structure are in general not available. However, a pragmatic definition of functional diversification is used. This distinguishes banks based on their observed revenue mix. 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. This will not bias the results, since 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 next subsection sets out the general methodology and 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 methodological and an economic point of view.

5.1 The baseline equation

5.1.1 Explaining heterogeneity in tail-βs: the empirical set-up

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 bounded 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[5]. The independent variables, X, are averages over a six-year interval to match the time interval over which the dependent variable is estimated. For many banks, we obtain observations for several, but not all, subperiods, which result in an unbalanced panel. We apply robust regression techniques that 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 in a given period or at the country level. Furthermore, 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.

The baseline regression is specified as follows:

$$X\beta = c + \beta_1 Net\,Commission\,Income + \beta_2 Net\,Trading\,Income + \beta_3 Net\,Other\,Operating\,Income + \widetilde{X}\gamma \tag{8}$$

We distinguish banks based on their observed revenue mix. Therefore, 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. 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

[5]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.

coefficient on any other shares means that these activities contribute differently to banks' extreme systematic risk than interest-generating activities.

Next to investigating the impact of revenue diversity, we include a number of other bank-specific characteristics, $\widetilde{X}$. Summary statistics on the accounting variables are reported in Table 3. The net interest margin and the loans-to-asset ratio proxy respectively market power and specialization in traditional banking markets. They are alternative indicators of a bank's dependence on and importance in traditional banking markets. If a bank has a higher interest margin, it will be able to create more rents and it will protect these by engaging in less risky activities. The loans-to-asset ratio captures how specialized a bank is in traditional intermediation activities. Furthermore, a number of other ratios 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[6]. As a result, the coefficients on the other variables capture the full effect on banks' tail-β.

5.1.2 The relationship between revenue diversity and banking system stability

The results 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 more positive impact on banks' extreme risk measures than that coming 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 other operating 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 collaborate the finding that traditional banking activities are less risky. Banks with a higher interest margin or higher loans-to-asset ratio are perceived to be less

[6]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.

affected by extreme market shocks since higher values of these ratios reduce banks' tail betas. A large correlation coefficient between these variables inflates the standard errors of the corresponding coefficients, which renders insignificance of the coefficients at the 10% level. However, a Wald test of joint significance strongly rejects the hypothesis that they are jointly insignificant. A similar conclusion is obtained when excluding the loans-to-assets ratio. This renders a highly significant coefficient on the net interest margin. Hence, we can conclude that banks that profitably focus on lending activities are less prone to extreme systematic risk than diversified banks.

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[7]. 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.

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. Some variables that may suffer from reverse causality are the equity-to-asset ratio and return on equity if banks' capital buffers are eroded from unexpected losses due to the more riskier income activity. 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. Column 3 of Table 4 presents coefficients of the baseline regression in which the averages of the equity-to-asset ratio, the profitability measure and the share of trading income are replaced by the initial values of each subperiod. In Column 4 of Table 4, all accounting variables are measured as initial values. Some interesting conclusions can be drawn from this analysis. First, in both specifications, trading income is still significant, which indicates that trading income causally affects bank risk. The other alternative revenue shares also remain significant, although the impact of the initial share of other operating income on banks' tail-βs is much lower. 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

[7] This is a common finding (for ordinary betas) in the empirical banking literature. See e.g. Baele et al. (2007) and Castren et al. (2006).

period) are less affected by a crash in the stock market return index.

5.1.3 The 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, since we applied a logistic link function. Both the 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 Other Operating 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 10%. All else equal, this shift of 10% of total revenues from the interest activities to non-traditional banking activities yields an increase in the average bank's tail-β of 2 basis points. An expansion into non-traditional banking may be accompanied by a reduction in a bank's loans and consequently interest margins. This may further increase the tail-β. If non-traditional banking activities are more capital-intensive, this will exert a mitigating effect on bank's 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 2 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 0.035. The larger bank will have, all else equal, a 3.5% higher probability of a large drop in its stock return occurring if there is a large, negative shock to the European market return index.

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 Graph 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. When they are evaluated at the sample mean, the marginal impact of the non-traditional banking activities is fairly similar. However, the implied effects differ substantively when they are assessed at other values. The marginal effect of a change in one variable increases monotonous 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 0.215 at the sample mean (which is 26% of total income). The impact is only half as large, around 0.11, 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 0.33, which is three times larger than the bank in the latter case.

The six panels of Graph 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 0.215. 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 0.043 ($= 0.246 - 0.203$) 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 0.06 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 stories 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 other operating 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

As is often the case in empirical (corporate) finance or banking, we are often confronted with panel data. This may raise some issues. In a first subsection, we check whether the residuals are correlated, either across cross-sections or over time. If so, OLS standard errors will be biased. In general there are two approaches to solve this problem. One can cluster the standard errors or one can implement the Fama-MacBeth procedure (for a recent survey article, see Petersen, 2007). Second, the panel data set is unbalanced. In general, unbalancedness is not a problem as long as selection into the sample is random. However, 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. We will deal with these issues in a second subsection.

5.2.1 Panel assumptions

The panel data at hand have three dimensions. We observe multiple banks from different countries over multiple periods. This may result in residuals that are correlated across observations, which will cause OLS standard errors to be biased. The traditional approach in empirical banking studies is to allow for within cluster correlation. Since there is often little theoretical guidance, it is a priori difficult to determine which cluster level is the relevant one. The residuals of a given bank may be correlated across years. Alternatively, the residuals of a given year may be correlated across different banks. In our set-up, the residuals of a given bank may as well be correlated with another bank from the same country (even across years). Which dependencies are most important will, in general, vary across data sets. In Table 5, we present the standard errors for different clustering levels. The first column presents unclustered, White standard errors. This will serve as the benchmark. Subsequent columns contain clustered standard errors at the bank, time and country level. Columns 5 and 6 contain standard errors clustered on two dimensions, respectively the bank and time dimension and the country and time level.

The standard errors in Column 1 are very small and lead to highly significant coefficients (for all variables). Relying on these standard errors may, however, yield invalid inference. If there is only autocorrelation in the residuals or the independent variables for a given bank, the OLS standard errors are incorrect. Clustering at the bank level will then yield correct, but larger, standard errors. Column two shows that this is indeed the case. On average, the standard errors are almost twice as high compared to the White standard errors. Column 3 reports standard errors clustered at the Country level. The standard errors are either much larger than the White standard errors and in general higher or almost equal to the standard errors reported in Column 2. As a result of the larger standard errors, the coefficient of the net interest margin and the loans-to-assets ratio are individually insignificant. The importance of the time effect (after including time dummies) is small in this data set. This can be observed from the standard errors reported in Columns 3 to 5. First, standard errors clustered at the time dimension (Column 3) are not higher than the ones reported in the first column (if anything, they appear to be smaller). 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 procedure consists of estimating cross sectional regressions for each time period[8]. The last column, Column 7 of Table 5 reports Fama-MacBeth coefficients and standard errors[9]. The Fama-MacBeth standard errors are close to the (incorrect) standard errors clustered by time, as both methods are designed to account for dependence in the time dimension.

From this, we conclude that clustering the standard errors in the cross-section dimension is quite important. Notwithstanding the much larger standard errors, we are still able to establish significant relationships. Clustering at the bank or the country level does not yield qualitatively different conclusions. Both approaches lead to similar inference about the significance of the coefficients. After including time fixed effects, there is little evidence for the presence of a time effect in the residuals.

The triple dimension of the panel data also affects the extent to which we allow for unobserved heterogeneity. In the baseline regression, we include time dummies as well as country fixed effects to absorb unobserved heterogeneity in a given period or at the country level. We could also interact the time and country dummy. Doing so, we eliminate the maximum amount of information that is due to time-varying country-specific influences[10]. Interacting both dummy variables does not affect the coefficients of interest (or their significance). We did not include bank-specific fixed effects. Fixed effects at the bank level correspond to first differencing the variables at

[8]The coefficients and their significance in the cross-sectional regressions are remarkably stable over the different periods. This holds especially for the different revenue shares, bank size and the equity-to-assets ratio. The cost-income ratio and the profitability measure are only significant in half of the time periods. Estimation results are available upon request.

[9]The Fama-MacBeth coefficients correspond to the average of the cross-section estimates. The standard errors of the Fama-MacBeth coefficient equal the cross-sectional standard deviation divided by the square root of the number of time periods. The procedure is designed for panels with a large time dimension.

[10]The interaction of the time and country effect absorbs the impact of variables that equally affect all banks in a country in a given period. This can be: the macro-economic environment, the regulatory framework, the corporate default rate. Alternatively, we could include these variables rather than the interaction of the dummies. This could lead to interesting insights. However, some of these variables (especially those capturing the regulatory framework) are not available over the period 1992-2004. This may create an omitted variable bias.

the bank level. However, low variability in the first differences of the independent variables makes it more difficult (if not impossible) to estimate the coefficients and establish significant relationships. If the variance is low, regressions in changes may contain very little information about the parameters of interest, even if the cross-sectional variation is large (Arellano, 2003). In our set-up, the independent variables are averages of bank-specific ratios over moving windows of six years. Hence, by construction, their first differences will be small and will exhibit low variation. Not surprisingly, if we include bank-specific dummies, all variables (except bank profitability) become insignificant.

5.2.2 Unbalanced panel

Many banks are not included in all subperiods. This results in an unbalanced panel. If (non-)selection in the sample occurs randomly, then the results of the baseline regression are not subject to a selection bias. There are several reasons why we do not observe a bank over the entire sample period. 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 although (useful) stock price information is not available, accounting data are. Hence, we can 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. Each selection equation is modelled as a probit, where the left hand side variable is a dummy variable. The dummy is one if that bank-time observation is included in the final sample and zero otherwise. Columns 1-3 of Table 6 represent the selection equation for respectively illiquid banks, IPOs and delisted banks. Next to including the variables that appear in the treatment equation (the baseline), we additionally include as instrument a categorical variable for the type of statement that a bank files[11]. Subsequently, we compute the Inverse Mills ratio (or selection hazard) for each selection equation and incorporate them in the baseline equation. The results can be inspected in Column 4. First, none of the Inverse Mills ratios is significant at the traditional significance levels. The Inverse Mills Ratio of the IPO selection equation has the lowest p-value, namely, 0.125. Second, the coefficient on the share of trading income has become much larger, while the coefficients on the other revenue shares dropped slightly. Hence, accounting for non-randomness in the sample selection alters the marginal effects but not the significance. Third, until now, we consistently obtained that cost-inefficient banks are less risky. That is banks with a higher cost-to-income ratio have a lower tail-β. This relationship disappears completely. Most

[11] Theoretically, the model is identified without including additional explanatory variables that discriminate between selection in or out of the sample. However, identification then relies on the chosen functional form. Therefore, we include an additional instrument. We will consider other instruments as well. Discrimination between frequently and infrequently traded stocks may be achieved by controlling for the nominal value, the number of shares outstanding or the exchange. Delistings may be explained by accounting losses, the volatility of the return or nominal value. The decision to go public largely depends on the market conditions (Ritter and Welch, 2002; Pastor and Veronesi, 2005)

of the banks that went public during the sample period had strong state linkages before. These banks are typically less efficient, but less risky due to their strong ties with the government. Apparently, this causes the unexpected significance if the selection bias is not appropriately taken into account.

Another important source of unbalancedness are mergers and acquisitions. For these banks, we do not possess information before (for post-M&A entities) or after (for pre-M&A entities) the M&A. As a consequence, we cannot implement the Heckman model on the observations. We check the stability of the results by leaving out the banks that are involved in an M&A.

Columns 1-3 of table 7 contain the estimation results when respectively the pre-M&A entities, the post-M&A entities and 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 become larger, which only strengthens the findings of the baseline. The other columns, Columns 4-7, support the baseline results as well as the findings of the two-step selection procedure. In column 4-6, we exclude subsequently illiquid banks, banks that went public, and delisted banks. In column 7, we exclude all banks from the sample that are involved in any of the issues mentioned in this subsection.

To conclude, although the panel dataset is unbalanced, the sources of the missing values in the dataset do not affect the relationships of interest.

5.3 Robustness checks on the baseline equation

In this Section, we describe four extensions to the baseline regression to generalize the findings and to check the stability of our results. First, we will investigate whether large and complex banking groups exhibit a different extreme risk profile. This group of banks deserves particular attention when banking system stability is at stake. Second, we describe the results for a smaller set of financial institutions, i.e. the group of listed commercial banks and bank holding companies. While other specialization types are common in the set of listed banks in Europe, this is not the case in the US. Third, in the initial sample years, some banking industries experienced a severe banking crisis. It is of interest to understand if and to what extent this contaminates our general results. Finally, we report results for subsamples of banks with moderate and aggressive growth strategy.

A group of banks that deserve particular attention when banking system stability is at stake are large and complex banking groups (LCBGs)[12]. LCBGs are these banking groups whose size and nature of business is such that their failure and inability to operate would most likely have adverse implications for financial intermediation,

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

the smooth functioning of financial markets or other financial institutions operating within the system. Large and Complex Banking Groups may differ substantially from the other banks in the sample. Not only are they larger, they may exhibit differences in terms of asset-liability structure as well as revenue composition. A difference in means test between LCBGs and the other banks in the sample confirmed that the mean values of the variables were different. From a supervisory point of view, a more important issue is whether the established relationships between the bank-specific variables and their co-crash probabilities are significantly different for both groups. This would imply that the LCBGs should be treated and monitored differently when supervisors assess banking system stability. Column 1 of Table 8 reports the results when a dummy variable for being a LCBG is added to the baseline equation. Recall that although we are employing a parsimonious linear model, the logistic link function enables to capture both non-linear relationships and interaction effects. Hence discovering a significant coefficient for the dummy would not only mean that LCBGs have different co-crash probabilities but also that all relationships vary for this set of banks. The dummy variable is, however, insignificant. In Column 2, we explicitly interact the dummy variable with the three alternative revenue shares. None of the interacted coefficients enters the regression significantly. After controlling for numerous variables, there are no other peculiarities of LCBGs that would yield them a different extreme risk profile. Being a LCBG does not affect the relationships between the revenue variables and the co-crash probabilities. A similar change in the revenue structure of a LCBG and a non-LCBG will, all else equal, lead to a similar changes in these banks' tail beta.

The group of banks in the sample can be classified in various types. We consider a wide range of financial intermediaries ranging from commercial banks, savings banks, cooperative banks, mortgage banks, credit institutions to bank holding companies. More than a quarter of the listed banks in Europe are not a bank holding company or a commercial bank. This contrasts with the situation in the US, where the other banking types only constitute a small fraction of the total set of listed banks. It is of interest to get insight in whether the sample composition is a source of discrepancy. Column 3 of Table 8 shows that the relationships established in the baseline regression are robust in the subsample of commercial banks and bank holding companies. Hence, if a similar analysis for the US banking industry would yield different results, this cannot be attributed to the sample composition.

Some European countries have been confronted with a banking crisis[13] 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 4 of Table 8, we exclude a bank-time observation if this bank has been active in a coun-

[13] Information on the timing and magnitude of the crisis is obtained from the Worldbank Database of Banking Crises (Caprio, 2003).

try that experienced a banking crisis[14] during one of the six years of that time frame. In column 5, we eliminate a bank-time observation if this bank has been active in a country that experienced a systemic[15] crisis during one of the six years of that time frame. The results reported in Column 4 and 5 show that including the crisis periods does not affect the results. If anything, the coefficients on the alternative revenue shares become even larger, which further strengthens our findings.

Finally, we redo the analysis for subsets of banks based on their growth strategy. A large variability in total assets in a subperiod of 6 year may be an indication that banks pursued an aggressive growth strategy (potentially though M&As). We compute the normalized standard deviation of total assets for each bank in each time period and use this measure to split the sample in various subsamples. We consider the subsets of the steady growth banks (50% and 70% lowest variability in total assets) and aggressive growth banks (50% and 70% highest variability in total assets). The results are reported in Columns 6-9 of Table 8. The effect of size, profitability and cost efficiency is fairly similar across the different columns. However, the analysis also delivers substantially different results for moderate versus aggressive growth banks. The impact of the capital buffer and the net interest margin is much higher in banks that exhibit a more stable evolution in total assets. With respect to the revenue shares, all alternative revenue types exhibit a significant impact for aggressive growth banks. In the subset of banks with lower variability in total assets, the share of other operating income in total income is no longer significant. Moreover, the coefficients on commission income and trading income are slightly smaller. Banks with a steady growth strategy or profile will experience a smaller increase in their co-crash probability when shifting from interest income to non-interest income sources.

To conclude, almost all results are confirmed in different set-ups and are almost not affected by the sample composition or crisis events.

6 Conclusion

The banking sector is at the heart of every economy and is a particularly important sector for the stability of financial systems. As a result, central bankers and financial supervisors invest numerous resources in analyzing and safeguarding banking sector stability. Reliable indicators of banking system stability are of utmost importance.

[14] 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.

[15] The Worldbank labels two of the six banking crises as systemic: Finland (1992-1994) and Sweden (1992-1995). Note that we only report the years that occur in the sample period, some crises started earlier.

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-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 significantly from one another. Other indicators of bank specialization in traditional intermediation, such as the net interest margin and the loans-to-assets ratio collaborate 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 facilitate a better understanding of the risks being taken on 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.

References

[1] Arellano, M. (2003) "Panel Data Econometrics (Advanced Texts in Econometrics)." Oxford University press, p. 244.

[2] Baele, L. (2005). "Volatility Spillover Effect in European Equity Markets." Journal of Financial and Quantitative Analysis 40, 373-401.

[3] Baele, L., O. De Jonghe, and R. Vander Vennet (2007). “Does the stock market value bank diversification?” Journal of Banking and Finance, forthcoming.

[4] Bekaert, G., and C. R. Harvey. (1997). "Emerging equity market volatility." Journal of Financial Economics 43, 29–77.

[5] Caprio, G. (2003). "Episodes of systemic and borderline financial crises." Worldbank Database of Banking Crises.

[6] Castren O., T. Fitzpatrick and M. Sydow. (2006). "What drives EU banks’ stock returns? Bank-level evidence using the dynamic dividend-discount model." European Central Bank, WP 677.

[7] Danielsson, J., L. de Haan, L. Peng and C. G. de Vries. (2001). "Using a bootstrap method to choose the sample fraction in tail index estimation." Journal of Multivariate Analysis, 76, 226-248.

[8] Dewatripont, M., and J. Mitchell. (2005). "Risk-taking in financial conglomerates." Work in progress.

[9] Embrechts P., Klüppelberg, C., and Mikosch, T. (1997). "Modelling extremal events." Springer: Berlin.

[10] Fama, E., and J. MacBeth. (1973). “Risk, return and equilibrium: Empirical tests,” Journal of Political Economy 81, 607-636.

[11] Ferson, W.E., and C.R. Harvey. (1991). "The time variation of economic risk premiums." Journal of Political Economy 99, 385–415.

[12] Freixas, X., G. Loranth and A. Morrison. (2005). "Regulating financial conglomerates." CEPR Discussion paper 5036.

[13] Hartmann, P., S. Straetmans and C. G. de Vries (2006). "Banking system stability: a cross-atlantic perspective." in Risks of Financial Institutions, eds. Mark Carey and Rene Stulz; National Bureau of Economic Research Conference Report.

[14] Heckman, J.J. (1976). "The common structure of statistical models of truncation, sample selection, and limited dependent variable models and a simple estimator for such models." Annals of Economic and Social Measurement 5, 475-492.

[15] Hill, B. M. (1975). "A simple general approach to inference about the tail of a distribution." The Annals of Statistics, 3, 1163-1173.

[16] Houston, J.F., and K.J. Stiroh (2006). “Three decades of financial sector risk”. Federal Reserve Bank of New York, Staff Reports.

[17] Kieschnick, R., and B.D. McCullough (2003). "Regression analysis of variates observed on (0, 1): percentages, proportions and fractions." Statistical Modelling 3, 193-213.

[18] Kwan, S.H. and E. S. Laderman. (1999). “On the portfolio effects of financial convergence: A review of the literature.” Federal Reserve Bank of San Francisco Economic Review 2, 18-31.

[19] Ledford, A., Tawn J. (1996). "Statistics for near independence in multivariate extreme values." Biometrika 83, 169-187.

[20] Lepetit, L., E. Nys, P. Rous and A. Tarazi (2006). “Product diversification in the European banking industry: risk and loan pricing implications.” Work in progress.

[21] Papke, L.E., and J.M. Wooldridge (1996). "Econometric Methods for Fractional Response Variables With an Application to 401 (K) Plan Participation Rates." Journal of Applied Econometrics 11, 619-632.

[22] Pastor, L., and P. Veronesi. (2005). "Rational IPO Waves.” Journal of Finance 60, 1713–1757.

[23] Petersen, M. (2007). "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches." Work in progress.

[24] Poon, S.-H., M. Rockinger and J. Tawn. (2004). "Extreme value dependence in financial markets: Diagnostics, models and financial implications." Review of financial studies 68, 581-610.

[25] Rajan, R.G. (2006). “Has financial development made the world riskier?” European Financial Management 12, 499-533.

[26] Saunders, A. and I. Walter. (1994). “Universal banking in the United States.”, Oxford, Oxford University Press.

[27] Schoenmaker, D., J.F. Slijkerman, and C.G. de Vries. (2005). "Risk diversification by European Financial Conglomerates." Tinbergen Institute Discussion Paper 2005, 110/2.

[28] Ritter, J.R., and I. Welch. (2002). "A review of IPO activity, pricing, and allocations." Journal of Finance 57, 1795-1828.

[29] Stiroh, K.J. (2004). “Diversification in banking: Is noninterest income the answer?”Journal of Money, Credit, and Banking 36, 853-882.

[30] Stiroh, K.J. (2006). “A Portfolio View of Banking with Interest and Noninterest Activities.” Journal of Money, Credit and Banking 38, 1351-1362.

[31] Stiroh, K.J. and A. Rumble. (2006). “The Darkside of Diversification: The Case of US Financial Holding Companies.” Journal of Banking and Finance 30, 2131-2161.

[32] Straetmans, S., W. Verschoor and C. Wolff. (2007). “Extreme US stock market fluctuations in the wake of 9/11.” Journal of Applied Econometrics, forthcoming.

Table 1: Unconditional Value at Risk

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

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	-0.253	-0.253	-0.182	-0.177	-0.193	-0.177	-0.195	-0.195
10th percentile	-0.185	-0.180	-0.172	-0.152	-0.161	-0.157	-0.159	-0.163
25th percentile	-0.121	-0.134	-0.136	-0.125	-0.129	-0.136	-0.139	-0.126
50th percentile	-0.091	-0.114	-0.103	-0.098	-0.106	-0.111	-0.110	-0.100
75th percentile	-0.073	-0.083	-0.078	-0.076	-0.078	-0.082	-0.086	-0.071
90th percentile	-0.052	-0.058	-0.052	-0.055	-0.055	-0.066	-0.062	-0.055
95th percentile	-0.046	-0.046	-0.040	-0.032	-0.036	-0.050	-0.057	-0.048
mean	-0.115	-0.126	-0.113	-0.107	-0.116	-0.111	-0.115	-0.107
standard deviation	0.082	0.080	0.066	0.072	0.096	0.041	0.049	0.053
number of obs.	106	120	124	130	121	124	128	132

Note: this table contains information on the unconditional Value at Risk for different time periods. Panel A provides the results for the European stock market index. Panel B reports 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%.

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	0.03	0.05	0.03	0.01	0.04	0.06	0.04	0.02
10th percentile	0.06	0.13	0.13	0.03	0.14	0.14	0.11	0.05
25th percentile	0.41	1.12	0.70	0.44	0.63	0.68	0.48	0.28
50th percentile	2.27	7.40	7.17	4.50	8.50	5.66	4.75	2.30
75th percentile	10.92	25.00	21.91	16.72	22.61	18.49	15.48	11.96
90th percentile	20.30	42.34	38.09	28.92	36.41	27.92	25.48	22.62
95th percentile	30.94	52.73	46.86	34.34	47.83	32.23	28.45	31.92
mean	7.91	15.42	14.26	11.18	14.14	10.73	9.16	8.13
standard deviation	13.25	18.10	17.50	14.28	16.44	12.16	11.28	12.81
number of obs.	106	121	126	131	122	126	130	135

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

	number of observations	mean	standard deviation	5th percentile	25th percentile	median	75th percentile	95th percentile
Interest Income	999	0.612	0.171	0.242	0.558	0.638	0.702	0.857
Commission and Fee income	999	0.261	0.145	0.033	0.184	0.252	0.313	0.518
Trading Income	999	0.056	0.064	0.000	0.014	0.043	0.076	0.156
Other Operating Income	999	0.061	0.092	0.000	0.001	0.037	0.076	0.220
Net Interest Margin	999	0.027	0.013	0.007	0.018	0.026	0.034	0.052
Loans-to-Assets	999	0.568	0.171	0.255	0.476	0.565	0.691	0.826
log Total Assets	999	9.412	1.939	6.493	8.033	9.286	10.713	12.871
Equity-to-Assets	999	0.073	0.067	0.024	0.045	0.059	0.081	0.152
Cost-to-Income	999	0.639	0.141	0.392	0.571	0.644	0.716	0.858
Return on Equity	999	0.114	0.096	0.012	0.075	0.114	0.161	0.225

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 asset-based measure of functional diversification. The last four rows provide summary statistics on the other control variables. The summary statistics provided are computed for the unbalanced panel of bank-time observations that enter the baseline regression.

Table 4: Drivers of heterogeneity in banks' tail betas

	Baseline regression	Marginal effects at sample mean	Baseline regression (ratios in grey boxes are measured as initial values	Baseline regression (ratios in grey boxes are measured as initial values
Constant	-2.6820***		-2.0515*	-2.7849***
	[0.8692]		[1.0579]	[0.6557]
Commission and Fee income	3.4676***	0.215177	2.8751***	3.0326***
	[0.8750]		[0.8698]	[0.6990]
Trading Income	3.6836***	0.2285845	2.2572***	2.3638***
	[0.9710]		[0.6453]	[0.6669]
Other Operating Income	4.1580***	0.258018	3.0144***	1.6398*
	[1.1351]		[0.9442]	[0.8519]
Net Interest Margin	-10.8047	-0.6704728	-8.5620*	-6.8769*
	[6.6710]		[4.6100]	[3.5946]
Loans-to-Assets	-0.899	-0.0557883	-1.5138	-1.1573**
	[1.0231]		[1.1370]	[0.5671]
Size	0.5345***	0.0331654	0.5179***	0.5096***
	[0.0582]		[0.0642]	[0.0662]
Equity-to-Assets	-6.2141***	-0.3856103	-7.1931***	-6.9703***
	[1.9389]		[1.8797]	[1.5480]
Cost-to-Income	-1.1226**	-0.0696597	-1.1586**	0.0111
	[0.4934]		[0.5248]	[0.3899]
Return on Equity	1.9043***	0.1181685	0.5203***	0.5177***
	[0.5470]		[0.0835]	[0.0912]
Time and Country fixed effects included				
Observations	1006		1006	1006
Number of bankid	189		189	189
R-squared	0.726		0.725	0.72

Standard errors in brackets (clustered at country level)
Generalized linear model, link function (logistic) - Quasi-ML estimates
* significant at 10%; ** significant at 5%; *** significant at 1%

Note: The first column reports the results for the benchmark regression. In this regression, the dependent variable, the tail-β, provides an indication of that bank's extreme systematic risk over a period of 6 year. The co-crash probability is bounded between [0,1]. Therefore, we employ a generalized linear model, estimated using quasi-maximum likelihood. 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 to mitigate the effect of outliers in the dataset. Moreover, in each regression, we include time dummies as well as country fixed effects to capture unobserved heterogeneity at the country level or in a given period. 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 and fourth column report results for variations on the benchmark equation. If a coefficient is reported in a grey box, this means that this ratio is not measured as the average over a 6 year period but rather as the initial value at the beginning of that period.

Table 5: Baseline regression coefficients and Standard errors clustered at different levels

	No clustering - only White corrected standard errors	Residuals are clustered at the bank level	Residuals are clustered at the country level	Residuals are clustered at the time level	Residuals are clustered at the bank & time level	Residuals are clustered at the country & time level	Fama McBeth coefficients and standard errors
Constant	-2.6820***	-2.6820***	-2.6820***	-2.6820***	-2.6820***	-2.6820***	-2.2360***
	[0.3815]	[0.6789]	[0.8692]	[0.2698]	[0.6230]	[0.8263]	[0.1915]
Commission and Fee	3.4676***	3.4676***	3.4676***	3.4676***	3.4676***	3.4676***	3.6446***
income	[0.3814]	[0.6988]	[0.8750]	[0.3535]	[0.6840]	0.86323405	[0.4686]
Trading Income	3.6836***	3.6836***	3.6836***	3.6836***	3.6836***	3.6836***	4.1586***
	[0.5869]	[0.9293]	[0.9710]	[0.4511]	[0.8501]	[0.8956]	[0.5164]
Other Operating	4.1580***	4.1580***	4.1580***	4.1580***	4.1580***	4.1580***	4.144***
Income	[0.7901]	[1.2123]	[1.1351]	[0.3897]	[0.9987]	[0.9034]	[0.3257]
Net Interest Margin	-10.8047**	-10.8047	-10.8047	-10.8047***	-10.8047	-10.8047*	-6.8330375
	[4.6491]	[8.2325]	[6.6710]	[2.6433]	[7.2902]	[5.4659]	[5.9996]
Loans-to-Assets	-0.8990**	-0.899	-0.899	-0.8990***	-0.899*	-0.899	-1.4187***
	[0.3500]	[0.5979]	[1.0231]	[0.1764]	[0.5159]	[0.9775]	[0.3008]
Size	0.5345***	0.5345***	0.5345***	0.5345***	0.5345***	0.5345***	0.5261***
	[0.0249]	[0.0464]	[0.0582]	[0.0247]	[0.04628]	[0.0581]	[0.0232]
Equity-to-Assets	-6.2141***	-6.2141***	-6.2141***	-6.2141***	-6.2141***	-6.2141***	-7.2090***
	[0.8154]	[1.4836]	[1.9389]	[0.8305]	[1.4919]	[1.9453]	[1.0732]
Cost-to-Income	-1.1226***	-1.1226**	-1.1226**	-1.1226***	-1.1226**	-1.1226**	-1.3960***
	[0.3131]	[0.5484]	[0.4934]	[0.1188]	[0.4656]	[0.3994]	[0.1838]
Return on Equity	1.9043***	1.9043***	1.9043***	1.9043***	1.9043***	1.9043***	1.3973***
	[0.3880]	[0.5909]	[0.5470]	[0.3100]	[0.5429]	[0.4947]	[0.3920]
Time and Country fixed effects included							
Observations	1006	1006	1006	1006	1006	1006	1006
Number of bankid	189	189	189	189	189	189	189
R-squared	0.726	0.726	0.726	0.726	0.726	0.726	0.726
Level of clustering:	not (White)	bank	country	time	bank & time	country & time	Fama McBeth
Generalized linear model, link function (logistic) - Quasi-ML estimates							
* significant at 10%; ** significant at 5%; *** significant at 1%							

Note: The table presents information on the baseline regression. The coefficients are the same across columns (except for the last column). The standard errors differ across specifications due to a different level of clustering of the residuals. The first column reports the results for the benchmark regression when the residuals are not clustered. However, the standard errors are only corrected for heteroscedasticity. In column 2-4, the standard errors are clustered in one dimension; respectively at the bank, country and time dimension. In column 5 and 6, two dimensional clustering of the residuals provides additional information on the correlation structure of the residuals of the panel set-up The last column contains coefficients and standard errors obtained using the Fama-MacBeth procedure (1973). The coefficients are obtained as time averages of T cross-sectional regressions, where T is the number of time frames. The standard errors equal the standard deviation of the T cross-sectional coefficients, divided by the square root of the number of time frames. In each regression, the dependent variable, the tail-β, provides an indication of that bank's extreme systematic risk over a period of 6 year. The co-crash probability is bounded between [0,1]. Therefore, we employ a generalized linear model, estimated using quasi-maximum likelihood. 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 to mitigate the effect of outliers in the dataset. Moreover, in each regression, we include time dummies as well as country fixed effects to capture unobserved heterogeneity at the country level or in a given period.

Table 6: Unbalancedness of panel: two-step Heckman selection model

	Selection equation for banks that are excluded because of illiquidity of its share	Selection equation for banks that go public during the sample period	Selection equation for banks that are delisted during he sample period	Baseline equation in which selection effects due to Illiquidity, IPO, delisting are taken into account
Constant	4.8596***	3.4387***	0.1081	-0.0154
	[1.0298]	[0.6527]	[0.9118]	[2.2465]
Commission and Fee income	9.1256***	-0.2381	-1.3912	3.0756***
	[1.0294]	[0.6839]	[0.8972]	[0.9516]
Trading Income	15.1475***	-2.8018***	-2.3458	5.1574**
	[2.3316]	[1.0320]	[1.4884]	[2.0481]
Other Operating Income	14.4810***	2.1055*	6.6849**	3.2968**
	[2.9524]	[1.1507]	[3.2625]	[1.3153]
Net Interest Margin	-42.8461***	-0.865	-1.6273	-8.8038
	[5.1265]	[6.7783]	[12.5719]	[8.6432]
Loans-to-Assets	-0.1918	-1.2868**	2.0702***	-0.2554
	[0.7626]	[0.5074]	[0.7799]	[1.0448]
Size	1.5450***	0.1096**	0.1715**	0.4702***
	[0.1451]	[0.0439]	[0.0824]	[0.0622]
Equity-to-Assets	-26.9224***	2.0688	4.0739	-6.0259***
	[2.9634]	[1.8181]	[3.0202]	[1.9661]
Cost-to-Income	-1.8770**	-1.8513***	1.7741*	-0.0455
	[0.8605]	[0.5079]	[0.9470]	[0.3693]
Return on Equity	-0.1485	0.0906	-2.0166	1.8152***
	[1.3557]	[0.7455]	[1.8596]	[0.6401]
Type of statement (1 if unconsolidated)	0.2834 [0.2024]	-0.1356 [0.1735]	-0.4788 [0.3315]	
Inverse Mills ratio Delisted				2.7759
				[3.5390]
Inverse Mills ratio IPO				-11.0711
				[7.2135]
Inverse Mills ratio Illiquid				-3.4128
				[4.3648]
Time and Country fixed effects included				
Observations	1268	1090	1027	1006
Number of bankid	220	189	189	189
R-squared (pseudo R2 for probit)	0.7892	0.0794	0.2447	0.73
Standard errors in brackets (clustered at country level incolumn 4)				
(Column 4): Generalized linear model, link function (logistic) - Quasi-ML estimates				
* significant at 10%; ** significant at 5%; *** significant at 1%				

Note: The table presents information on the impact of sample selection issues on the baseline regression. The panel is unbalanced and the nature of being selected into the sample may not be random. Events that may create a sample selection problem are e.g. the exclusion of infrequently traded stock (illiquidity), IPOs or delistings. Therefore, we implement a two-step Heckman selection model. In the first step, the determinants of being included/excluded are estimated using a binary dependent variable model. The first three columns report the results of a probit in which the dummy variable is zero if: (i) a bank's share is traded infrequently (column 1), (ii) the bank-time observations prior to the IPO are observed (for banks that went public during the sample period) (column 2), (iii) the bank-time observation after a delisting are observed (for banks that were delisted during the sample period) (column 3). For each of the selection equations, we compute the Inverse Mills Ratio. These three ratios are added to the baseline regression to examine the potential impact of a non-random selection bias on the established relationships. The results of this second step in Heckman's selection model are reported in Column 4. In column 4, the dependent variable, the tail-β, provides an indication of that bank's extreme systematic risk over a period of 6 year. The co-crash probability is bounded between [0,1]. Therefore, we employ a generalized linear model, estimated using quasi-maximum likelihood. 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 to mitigate the effect of outliers in the dataset. Moreover, in each regression, we include time dummies as well as country fixed effects to capture unobserved heterogeneity at the country level or in a given period. Standard errors take into account groupwise heteroscedasticity.

Table 7: Unbalancedness of sample: subsamples

	Exclude pre-M&A entities from sample	Exclude post-M&A entities from sample	Exclude pre-M&A and post M&A entities from sample	Exclude banks whose share is illiquid in one of the time windows	Exclude banks that go public in sample period	Exclude banks that are delisted during the sample period	Exclude banks that have been involved in M&A, IPO, Delisting or which share is illiquid
	bt_eu	bt_eu	bt_eu	bt_eu	bt_eu	bt_eu	bt_eu
Constant	-2.6419***	-3.0156***	-3.1477***	-2.6845***	-3.0180***	-2.5619***	-3.3494***
	[0.7483]	[0.7948]	[0.6951]	[0.8697]	[0.8052]	[0.8555]	[0.6319]
Commission and	3.8890***	3.8582***	4.4467***	3.4639***	3.5288***	2.9605***	4.0493***
Fee income	[0.9338]	[0.7715]	[0.6904]	[0.8741]	[0.8395]	[0.6754]	[0.5049]
Trading Income	4.2997***	4.7050***	5.8683***	3.6924***	3.4545***	3.6169***	5.3348***
	[1.2438]	[1.1922]	[1.4585]	[0.9699]	[0.8419]	[1.0143]	[1.7564]
Other Operating	4.8580***	5.3120***	6.4750***	4.1574***	4.1745***	3.8647***	6.7713***
Income	[1.2415]	[1.0177]	[0.7722]	[1.1356]	[1.2118]	[1.1164]	[0.8698]
Net Interest	-7.5006	-10.5379	-5.9078	-10.4662	-13.3303***	-9.6911	-3.2629
Margin	[7.4655]	[6.4142]	[7.5068]	[6.7704]	[4.7799]	[7.1052]	[5.9486]
Loans-to-Assets	-0.8059	-0.6699	-0.444	-0.9032	-0.5587	-1.2136	-0.7093
	[1.0226]	[0.9194]	[0.9089]	[1.0238]	[0.8832]	[1.0197]	[0.7555]
Size	0.5412***	0.5691***	0.5899***	0.5336***	0.5278***	0.5461***	0.5987***
	[0.0725]	[0.0594]	[0.0737]	[0.0583]	[0.0520]	[0.0618]	[0.0745]
Equity-to-Assets	-6.3548***	-6.7852***	-7.1333***	-6.2081***	-5.4992***	-6.3134***	-7.1010***
	[2.1493]	[1.5890]	[1.7272]	[1.9396]	[1.8339]	[1.8823]	[1.5306]
Cost-to-Income	-1.7220***	-1.2843***	-1.9836***	-1.1268**	-0.8177**	-0.9800**	-1.6127***
	[0.6624]	[0.4823]	[0.6246]	[0.4942]	[0.4006]	[0.4221]	[0.5350]
Return on Equity	1.8634***	2.0142***	2.0722***	1.8933***	1.9923***	1.9801***	2.1787***
	[0.5030]	[0.5010]	[0.4699]	[0.5503]	[0.5688]	[0.5426]	[0.4674]
Time and Country fixed effects included							
Observations	875	929	805	990	944	972	724
Number of bankid	157	170	139	181	160	181	109

Standard errors in brackets (clustered at country level)
Generalized linear model, link function (logistic) - Quasi-ML estimates
* significant at 10%; ** significant at 5%; *** significant at 1%

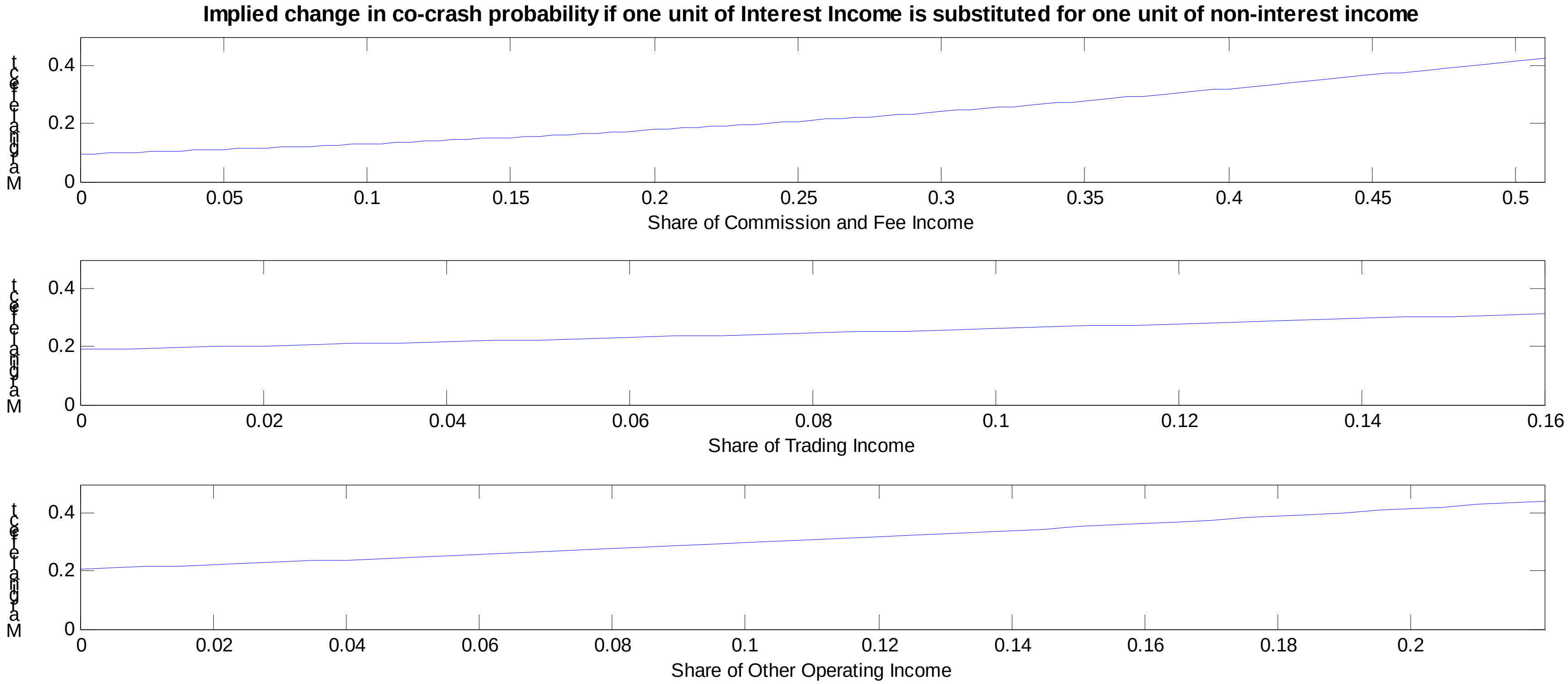
Note: The table presents information on the stability of the baseline results in various subsamples. In Column 1-3, we check whether M&As that occurred during the sample period affect the results. We estimate the baseline regressions respectively without the banks that constitute the separate entities before the M&A, without the resulting new entity after the M&A, and both. In columns 4-6, we eliminate the banks whose shares have been illiquid in previous sample periods, banks that go public and banks that are delisted. In the last column, we redo the analysis and include only those banks that were not involved in one of the aforementioned events. In the regressions, the dependent variable, the tail-β, provides an indication of that bank's extreme systematic risk over a period of 6 year. The co-crash probability is bounded between [0,1]. Therefore, we employ a generalized linear model, estimated using quasi-maximum likelihood. 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 to mitigate the effect of outliers in the dataset. Moreover, in each regression, we include time dummies as well as country fixed effects to capture unobserved heterogeneity at the country level or in a given period. Standard errors take into account groupwise heteroscedasticity.

Table 8: Subsample stability: the effect of bank type, banking crises or growth strategy

	Include LCBG dummy	Include LCBG dummy and interact with revenue shares	Subset of commercial banks and bank holding companies	Exclude banking crisis from sample	Exclude systemic banking crisis episodes from sample	Banks with standardized volatility of total assets below 70th percentile	Banks with standardized volatility of total assets below 50th percentile	Banks with standardized volatility of total assets above 50th percentile	Banks with standardized volatility of total assets above 70th percentile
Constant	-2.6828***	-2.7563***	-1.9480*	-2.8966***	-2.6484***	-1.5724**	-1.3620*	-3.9439***	-3.3931***
	[0.8399]	[0.9222]	[1.0289]	[0.7028]	[0.8717]	[0.7837]	[0.7867]	[0.8701]	[0.6805]
Commission and Fee	3.2810***	3.4059***	3.1127***	3.9472***	3.5192***	2.5706***	2.5345***	4.7967***	4.0045***
income	[0.8246]	[0.7924]	[1.0146]	[0.9020]	[0.8770]	[0.6135]	[0.6367]	[1.2835]	[0.9706]
Trading Income	3.3457***	3.6183**	2.8983***	4.1962***	3.7477***	2.0974**	3.1724*	3.6624***	3.2833***
	[1.1194]	[1.4128]	[1.0247]	[0.8641]	[0.9729]	[1.0020]	[1.6773]	[1.0014]	[0.8297]
Other Operating	3.8815***	3.5203***	3.6931***	4.8723***	4.3481***	0.2318	0.8303	4.9273***	4.3052***
Income	[1.1940]	[1.3355]	[1.0763]	[1.2524]	[1.1245]	[1.1695]	[2.1915]	[1.2429]	[1.0972]
Net Interest Margin	-12.4482**	-12.6097**	-17.7883***	-15.0244***	-10.2073	-15.1515***	-20.7886***	-4.2689	-9.0453
	[5.5433]	[5.1021]	[6.6343]	[5.8043]	[6.7035]	[4.7471]	[3.9354]	[12.8118]	[9.3420]
Loans-to-Assets	-0.7976	-0.7723	-0.7782	-0.3104	-0.927	-1.582	-1.3594	0.1452	-0.431
	[0.9771]	[0.9376]	[0.9045]	[0.7486]	[1.0240]	[1.0217]	[1.2222]	[0.8865]	[0.7880]
Size	0.5025***	0.5041***	0.5167***	0.5315***	0.5357***	0.5319***	0.5602***	0.5910***	0.5795***
	[0.0485]	[0.0476]	[0.0538]	[0.0634]	[0.0592]	[0.0547]	[0.0720]	[0.0822]	[0.0667]
Equity-to-Assets	-5.5789***	-5.7026***	-5.7116***	-5.1052***	-6.2957***	-7.3535***	-7.2683***	-2.9211*	-2.9792*
	[1.5791]	[1.5069]	[2.0636]	[1.8208]	[1.9425]	[0.8725]	[1.1920]	[1.6469]	[1.5494]
Cost-to-Income	-1.0888**	-1.0389**	-1.6229***	-1.1538**	-1.1860**	-1.3342***	-1.4507***	-1.2805**	-1.1995***
	[0.4725]	[0.4979]	[0.6280]	[0.4864]	[0.5045]	[0.3657]	[0.4284]	[0.5054]	[0.3935]
Return on Equity	1.8728***	1.9086***	1.5917**	2.3691***	1.7892***	1.9216***	2.5174***	1.7900***	1.8830***
	[0.5603]	[0.5842]	[0.6506]	[0.5858]	[0.5205]	[0.4313]	[0.5744]	[0.6387]	[0.4134]
Dummy LCBG	0.2157	0.8069							
	[0.3287]	[0.9665]							
Commission and Fee		-2.3978							
income * Dummy LCBG		[2.2821]							
Trading Income *		-0.2961							
Dummy LCBG		[1.7526]							
Other Operating		2.0231							
Income * Dummy LCBG		[3.8322]							
Time and Country fixed effects included									
Observations	1006	1006	756	791	983	701	500	499	700
Number of bankid	189	189	142	174	187	166	139	128	161
Standard errors in brackets (clustered at country level); * significant at 10%; ** significant at 5%; *** significant at 1%									
Generalized linear model, link function (logistic) - Quasi-ML estimates									

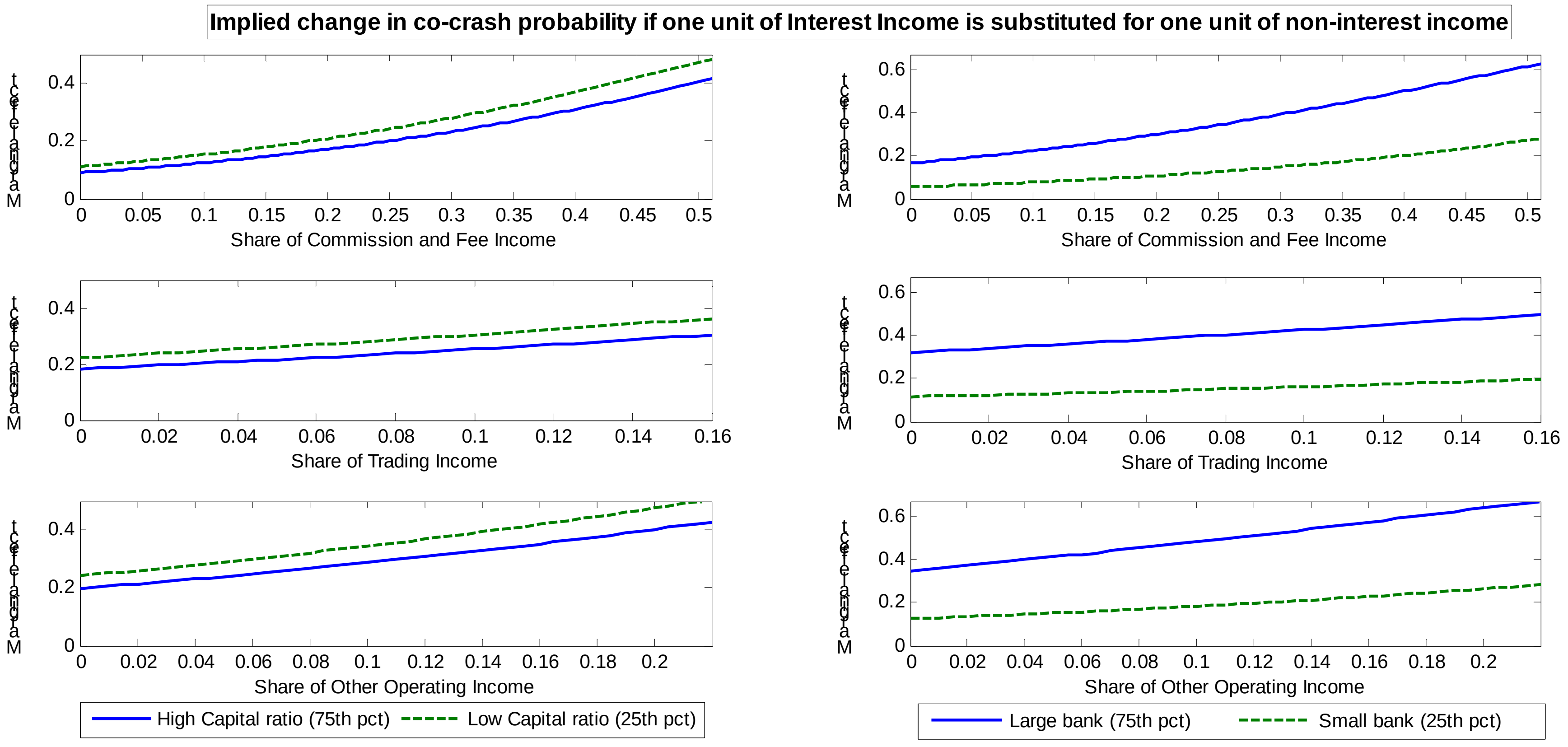
Note: The table presents information on the stability of the baseline results in various subsamples. In Column 1-3, we check whether specific bank types affect the established relationships. In column 1, we include a dummy variable for Large and Complex Banking Groups. In column 2, this dummy variable is also interacted with the different revenue shares. Column 3 presents the results for the set of Commercial banks and Bank Holding Companies. These bank types make the set of banks more comparable to the set of listed US banks. In Column 4, 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 column 5, we restrict this exclusion criterion to systemic banking crises. Finally, we compute the normalized standard deviation of total assets for each bank in each time period and use this measure to split the sample in various subsamples. Columns 6-9 present the estimation results for sets of banks with different growth strategies. We consider respectively the banks with standardized volatility of total assets below 70th percentile (exclude fast growing banks), below the 50th percentile (exclude moderate and fast growing banks), above the 50th percentile (exclude slow growing banks) and above the 30th percentile (exclude stable banks). In all regressions, the dependent variable, the tail-β, provides an indication of that bank's extreme systematic risk over a period of 6 year. The co-crash probability is bounded between [0,1]. Therefore, we employ a generalized linear model, estimated using quasi-maximum likelihood. 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 to mitigate the effect outliers in the dataset. Moreover, in each regression, we include time dummies as well as country fixed effects to capture unobserved heterogeneity at the country level or in a given period. Standard errors take into account groupwise heteroscedasticity.

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.