IV SPECIAL FEATURES

A BANK INCOME DIVERSITY AND SYSTEMIC RISK

Since the enaction of the Second Banking Directive of 1989, European banks have been permitted to engage in any degree of functional diversification that they consider optimal in terms of risk and return. From a financial stability assessment perspective, it is useful to ask how functional diversification affects risk in the banking system. This Special Feature uses statistical techniques to generate a market-based risk measure, and examines how developments in banks' income components affect this risk measure during times of extreme equity market movements. The main findings are that size and trading income have a positive effect on the systemic risk measure used, while income from traditional intermediation activities is negatively related to the risk measure used.

INTRODUCTION

In Europe, banks' business activities span the areas of banking, securities and insurance. The main regulatory measure that governs these activities is the Second Banking Coordination Directive, which was enacted in 1989. The Directive was intended to create a level playing-field for banks in terms of competition by introducing a single banking license within the EU. This also laid the groundwork for the functional diversification of European banks. Since then, banks have been allowed to operate broad franchises, combining commercial banking, securities, insurance and other financial activities in one business entity.

As a result of these regulatory changes, European banks have been pursuing a variety of different business strategies since the early 1990s. Some have opted to remain active in traditional financial intermediation, focusing on branch-based lending and deposit-taking. By contrast, others have diversified into investment banking, a development comparable to that in the US, where some large banks have set up investment banking subsidiaries.[1]

Several European banks have pursued pan-European and global strategies in investment banking, in some cases expanding through acquisitions. The range of diversified financial groups in Europe extends well beyond investment banking, however. A number of banks have opted for the so-called bancassurance model, combining commercial banking and insurance activities, both underwriting and distribution. Moreover, a large number of banks are also active in brokerage activities, asset management, corporate finance and venture capital. All these non-traditional activities generate non-interest revenues in the form of fees, commission income or trading income.

The issue of how these different business models evolve is important to several stakeholders. A bank's management is concerned about how different revenue streams contribute to bank profitability, both in the short and long term. Shareholders are interested both in this and in a bank's risk profile to the extent that diversification could affect the return on their investment. Finally, public authorities responsible for promoting financial stability are interested in how these developments influence the stability of the financial system.

This Special Feature focuses on how income diversity is related to extreme movements in banks' equity returns as a proxy for financial system stability. It reviews the relevant literature on the impact of revenue diversity on bank risk, and then discusses the measurement of tail risk, how it evolves, and income diversity measures. Subsequently, it provides empirical results and some robustness checks, before ending with some concluding remarks.

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1 Under US regulations, these are called Section 20 subsidiaries. These are regulated investment banking subsidiaries of a commercial bank that is eligible to conduct a range of investment banking activities in the US under specific powers granted by the Federal Reserve Board.

REVENUE DIVERSITY AND BANK RISK: A BRIEF REVIEW OF THE LITERATURE

The main idea behind revenue diversity is that a combination of banking, insurance and securities activities could lead to a more stable profit stream than a less diversified model. This is because the revenues from different business lines in a conglomerate are usually less than perfectly correlated. Earlier evidence for the US had already indicated that securities and insurance activities both have the potential to decrease earnings volatility, but that the effect largely depends on the type of diversifying activities that bank holding companies undertake.[2] Expanding banks' activities may reduce risk, with the main risk reduction gains arising from insurance rather than from securities activities.

However, more recent work has tended to find that the opposite is true.[3] For the US, studies using accounting data suggest that increased reliance on non-interest income raises the volatility of accounting profits without raising average profits significantly. There are only minor diversification benefits for bank holding companies, and these gains are offset by increased exposure to more volatile non-interest income activities for more diversified US banks.

Results based on US equity data arrive at a similar conclusion.[4] 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 reliance on non-interest income.

Some evidence suggests that European banks with a greater share of non-interest income activities exhibit a higher level of risk than banks undertaking traditional intermediation activities. Risk is mainly positively correlated with the share of fee-based activities, but not with trading activities.[5] Studies on the effect of diversification on market-based measures of performance and riskiness (and the risk/return trade-off) have found that banks with a higher share of non-interest income in total income are perceived to perform better in the long run. Their franchise values, as measured by Tobin's Q ratio, are positively related to diversification.[6] More importantly, this diversification of revenue streams from different financial activities increases the systematic risk of banks, making the stock prices of diversified banks more sensitive to movements in a general stock market index than non-diversified ones.

To sum up, most of the available evidence identifies various relationships between functional diversification and bank risk in normal economic conditions. However, it is not yet clear how diversified financial institutions will behave in adverse economic situations, and what overall impact revenue diversification could have on banking sector stability in these circumstances. The remainder of this Special Feature therefore focuses exclusively on this aspect.

MEASURING BANKING SYSTEM RISK

The basic approach followed in this Special Feature consists in constructing a measure of

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2 Notwithstanding the fact that regulatory impediments to functional diversification were removed earlier and more completely in Europe, most of the empirical evidence is based on US data. See S. H. Kwan 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; and A. Saunders and I. Walter (1994), *Universal Banking in the United States*, Oxford: Oxford University Press.

3 See R. DeYoung and K. P. Roland (2001), "Product Mix and Earnings Volatility at Commercial Banks: Evidence from a Degree of Total Leverage Model", *Journal of Financial Intermediation*, 10, 54-84; K. J. Stiroh (2004), "Diversification in Banking: Is Non-interest Income the Answer?", *Journal of Money, Credit and Banking*, 36, 853-882; and K. J. Stiroh and A. Rumble (2006), "The Darkside of Diversification: The Case of US Financial Holding Companies", *Journal of Banking and Finance*, 30, 2131-2161.

4 See K. J. Stiroh (2006), "A Portfolio View of Banking with Interest and Non-interest Activities", *Journal of Money, Credit and Banking*, 38, 1351-1362.

5 See L. Lepetit, E. Nys, P. Rous and A. Tarazi (2006), "Product Diversification in the European Banking Industry: Risk and Loan Pricing Implications", mimeo.

6 See L. Baele, O. De Jonghe and R. Van der Vennet (2007), "Does the Stock Market Value Bank Diversification?", *Journal of Banking and Finance*, forthcoming.

extreme equity market movements and relating this measure to various income diversity measures. The methods draw on extreme systematic risk measures that have been discussed in previous issues of this Review.[7] Further detail is provided in Box A.1.

More specifically, tail betas are estimated for a large set of European banks. A tail beta is the estimated bivariate probability of a crash in a bank's stock return, and is conditional on a market-wide decline (details on how to estimate tail betas are provided in Box A.1). In one sense, it is the tail equivalent of the traditional systematic risk measures derived from asset pricing models.[8]

However, the tail beta measure differs in two main ways from the traditional market beta. First, the tail beta is in general not tied to a specific distribution. This contrasts with the traditional market beta, which has the disadvantage that it is a correlation-based measure based on the multivariate normal distribution. There is ample evidence to suggest that the marginal distributions of (bank) stock returns are not normally distributed, especially in the tail area (the area that represents large losses). As tail betas are based on statistical extreme value theory and are semi-parametric in nature, they do not depend on any distributional assumption. Second, since only the tail part is modelled, estimation only uses data from the tail area and hence is not biased towards the centre. The results are particularly useful for assessing the probability or magnitude of the most extreme negative outcomes.

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7   See ECB (2006), "Assessing banking system risk with extreme value analysis", *Financial Stability Review*, June. A more technical account is provided by P. Hartmann, S. Straetmans and C. de Vries (2005), "Banking System Stability: A Cross-Atlantic Perspective", in M. Carey and R. Stulz (eds), *The Risk of Financial Institutions*, Cambridge: NBER.
8   For a more detailed exposition, see S. Straetmans, W. Verschoor and C. Wolff (2007), "Extreme US Stock Market Fluctuations in the Wake of 9/11", *Journal of Applied Econometrics*, forthcoming.

Box A.1

MEASURING BANKING SYSTEM STABILITY USING EXTREME VALUE ANALYSIS

In this Special Feature, extreme value analysis is used to measure banking system stability. The focus is exclusively on extreme downturns in banks' equity returns. The risk measure is a multivariate one, and estimates the probability of a decline or crash in a bank stock index, conditional on a sharp decline in the market portfolio index. The resulting co-crash probabilities provide an indication of systematic risk during crisis periods. They can be seen as a tail equivalent to betas obtained in classical asset pricing models. More specifically, the aim is to obtain estimates of the probability of a large negative return in a bank's equity returns, conditional on a decline in the market index. This can be expressed formally by the following

expression: $P(X > x | Y > y) = \dfrac{P(X > x \cap Y > y)}{P(Y > y)}$,

where X is a bank's stock return (computed as the logarithmic first difference of a return index), Y is the return on the market index (the conditioning asset), and x and y are thresholds in the tail of the distributions. In common with the literature, the negative of the returns is used. The returns X and Y will have different marginal distributions. As a result, the threshold levels x and y will differ for the bank return index (X) and for the market return index (Y). The thresholds are defined such that unconditional events are equally unlikely to occur. This results in $P(X > x) = P(Y > y) = p$, where p denotes a very small probability. In this Special Feature, the quintiles are chosen so that the individual probability of a crash is 0.04%. This unconditional

probability serves as a benchmark to see whether both assets are dependent in the tails. Since the stock returns are observed at daily frequency, this corresponds to an event that happens on average once every decade (= the inverse of 250 times the crash probability of 0.04%).

As the risk measure is particularly interesting owing to its dependency structure, i.e. that X is conditional on Y, the impact of different marginal distributions has to be eliminated. To do this, the original returns series are transformed into series with a common marginal distribution. After this transformation, differences in joint tail probabilities across different banks can purely be attributed to differences in the tail dependency structure of the extremes. For reasons of comparability with the literature, the stock returns are transformed into unit Pareto marginals.[1] This transformation implicitly assumes that the threshold levels x and y are chosen so that the tail probabilities of the univariate events are all equal to p. This can, however, be generalised. The transformation of the return series affects the expression of the conditional probability as

follows: $P(\tilde{X} > q | \tilde{Y} > q) = \dfrac{P(\tilde{X} > q \cap \tilde{Y} > q)}{P(\tilde{Y} > q)} = \dfrac{P(\min(\tilde{X}, \tilde{Y}) > q)}{P(\tilde{Y} > q)}$.

The thresholds for both assets are now normalised to q as a result of transforming the returns series to series with a common marginal distribution. Furthermore, the probability that both assets could exceed the threshold simultaneously can now be rewritten as a probability that the minimum (given that the negative of the returns are considered) of the two series will exceed the threshold. If the lowest value of the pair $(\tilde{X}, \tilde{Y})$ exceeds the threshold, the other will exceed it as well. This reduces the estimation of the multivariate probability to a univariate set-up. The tail behaviour of this univariate minimum series mimics the behaviour of the joint tail. The univariate exceedance probability of the newly created minimum series – $\min(\tilde{X}, \tilde{Y})$ – can now be obtained using univariate extreme value analysis. The crucial parameter will be the tail index of this minimum series, which determines the fatness of the joint tail. This tail index is estimated with a modification of the well-known Hill estimator, and captures the decay of the joint probability mass far from the centre of the distribution. 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 the tail index and the number of observations used to estimate it. The intercept of this regression yields an unbiased estimate of the tail index (α). Note that, by using a large number of values of m, the number of observations that determine the tail region, this bias-corrected method is designed to reduce sensitivity to the single choice of m required by the Hill procedure. After estimating the optimal α, an automated grid search is performed 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.

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1 The empirical counterpart of transforming the stock returns to unit Pareto marginals is based on the following equation:
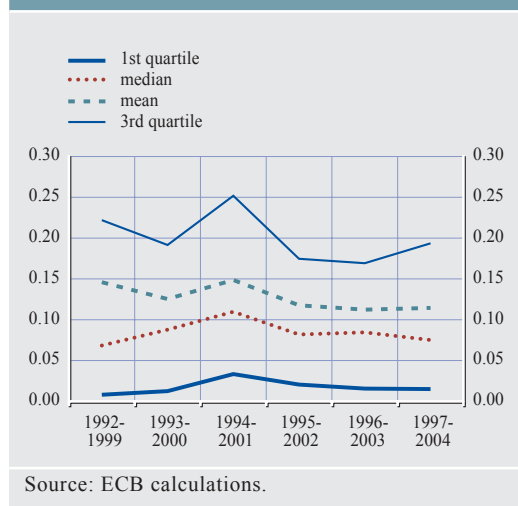
$\tilde{X}_i = \dfrac{n+1}{n+1-R_{X_i}}$, where i = 1,...,n and R_{X_i} is the rank order statistic of return X_i.

EXTREME RISK MEASURES

This Special Feature uses data from listed banks that have their headquarters in one of the EU15 countries. Furthermore, a number of selection criteria are imposed: only those banks for which at least eight years of information is available from Thomson Financial Datastream are included, and at least eight years of daily stock market returns are needed to measure these extreme risk indicators.

Chart A.1 Co-crash probabilities (tail beta)

- 1st quartile
- median
- mean
- 3rd quartile

Source: ECB calculations.

starts in a new calendar year) in the sample. Chart A.1 provides an indication of the time evolution of banks' tail betas, along with the mean, the median, and the 25th and the 75th percentiles of the estimated co-crash probabilities.

Three main observations can be made regarding the extreme risk measure. First, there is considerable cross-sectional heterogeneity over time, with the mean tail beta exceeding the median at each point in time. Although this gap has narrowed, it still remains substantial at around 5%. Second, at the beginning of the sample, the median tail beta increased from 7% to 10%, although in later periods, the mean and median levels declined and became rather stable towards the end of the sample. The median co-crash probability stabilised at 8%. Hence, when the return on the European market index declines, there is an 8% probability that a European bank will simultaneously experience an equally unlikely decline in its stock returns. Third, it seems that many banks have low co-crash probabilities and are thus only moderately vulnerable to market-wide shocks. Many banks have a tail beta (with respect to a broad European index) that is very close to zero. One explanation is that the least vulnerable banks are probably more exposed to local (country) shocks rather than regional

Since the focus is on both cross-sectional dispersion of bank risk as well as the evolution of risk over time, the sample is rearranged in moving eight-year windows. Following the usual conventions, a liquidity criterion is imposed on the bank stock returns, as infrequently traded stocks may not absorb information accurately.[9] Chart A.1 provides an indication of the evolution of the time series as well as the cross-sectional dispersion in the estimated tail betas for a sample of EU15 banks.

The vertical axis of Chart A.1 shows the conditional probability that a bank will experience an extreme stock price decline given an equally unlikely large decline in the market index. The values are chosen so that the individual probability of a crash is 0.04%. Since the stock returns are observed at daily frequency, this corresponds to an event that happens on average once every ten years (i.e. the inverse of 250 times the crash probability of 0.04%).

The horizontal axis shows the eight-year moving time intervals. The co-crash probabilities are computed over an eight-year period.[10] Moreover, for the banks that are present in the sample for more than eight years, the tail beta is estimated for each eight-year period (which

9 Stocks are only disregarded if they have more than 60% zero returns. Although bank stocks slightly below this figure are very illiquid, their non-zero returns could reflect micro-structure effects. Their inclusion does not affect the estimates of extreme risk.

10 The analysis is performed over the period 1992-2004. Only those banks for which at least eight years of information could be retrieved are included in the sample. Moreover, the 13-year sample period is split into moving sub-samples of eight years. For each sub-sample, one year of observations is removed from the sample and replaced by a more recent year for three reasons. First, looking at the same eight years for all banks facilitates comparison of the risk measures at a given point in time. Second, utilising this approach the number of observations for the second part of the analysis was increased. For interest, the results for various sub-periods are not changed substantially (see Table A.1, column (b)). Third, employing extreme value analysis requires a long time series to estimate the measures of tail risk. The choice of eight years is in line with the samples used in the literature.

(European-wide) shocks. This may be true in particular for the smaller banks.[11]

INCOME DIVERSIFICATION MEASURES

To construct the income diversity measures, balance sheet and income statement data on all banks with their headquarters in EU15 countries are needed. To this end, the stock market data were matched with the corresponding data from Bureau van Dijk's Bankscope to produce an unbalanced sample of 520 observations over the period 1992-2004. The independent variables are averages over an eight-year interval which is designed to match the time interval over which the dependent variable is estimated. Hence, the results should provide an indication of long-run relationships.

The main question posed in the introduction of this Special Feature was the extent to which different business activities affect banking system stability. 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 structures are in general not available either from Bankscope or from published financial results.

Instead, a pragmatic definition of functional diversification was used which distinguishes between banks based on their observed revenue mix. Total operating income is divided into four revenue classes: 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. This publicly available information forms the basis for analysts and investors to assess the long-term performance potential and risk profile of a bank.

The focus is on the differential impact that different revenue sources have on extreme bank risk. As the shares of net interest income, net commission and fee income, net trading income

and net other operating income sum to one, the share of net interest income is left out of the regression equation. This implies that if the coefficients on the other shares are significant, they are likely to exhibit a different risk profile than interest-generating activities.

A number of other bank-specific characteristics were also controlled for. The net interest margin and the loans-to-asset ratio proxy respectively market power and specialisation 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 may be able to create more rents, and could choose to protect these by engaging in less risky activities. The loans-to-asset ratio captures how specialised a bank is in terms of traditional intermediation activities. A cost efficiency variable was included as a control variable in an attempt to control for any possible relationships between risk and efficiency. A size variable was included to control for the possibility that larger banks may be more prone to market-wide events, and a capital buffer measure was included to control for the fact that better capitalised institutions may be less susceptible to market-wide events.

RESULTS

The results shown in Table A.1 reflect the relationships between various control variables and banks' tail beta measures.[12]

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11 This has some support (for ordinary betas) in the empirical banking literature. See L. Baele, O. De Jonghe and R. Van der Vennet (2007), "Does the Stock Market Value Bank Diversification?", *Journal of Banking and Finance*, forthcoming; and O. Castren, T. Fitzpatrick and M. Sydow (2006), "What Drives EU Banks' Stock Returns? Bank-level Evidence Using the Dynamic Dividend-discount Model", *ECB Working Paper*, No. 677.

12 Size and ROE are orthogonalised with respect to all other variables. The regressions always include time and country dummies, and the standard errors are clustered at the country level. Furthermore, the pooling of cross-sectional and time series data of multiple observations on a given bank implies that the data may no longer be independently distributed. Therefore, robust estimation methods that control for groupwise heteroscedasticity were used. In addition, the methods used allow for first-order autocorrelation of the error term, in order to take into account the fact that the tail betas are estimated for overlapping rolling time windows.

Table A.1 Drivers of tail beta: full sample

	Full sample (a)	1997-2004 sub-sample (b)
Constant	0.1983	-0.1264
	[0.322]	[0.154]
Commission and fee income	1.2120 **)	1.3357 *)
	[1.998]	[1.825]
Trading income	3.6292 ***)	4.0100 **)
	[3.522]	[2.547]
Other operating income	1.9656 *)	3.7453 **)
	[1.717]	[2.352]
Net interest margin	-0.3969 ***)	-0.3224 ***)
	[5.255]	[2.998]
Loans to assets	-1.9233 ***)	-2.6089 ***)
	[3.074]	[3.306]
Size	0.6763 ***)	0.4881 ***)
	[15.407]	[8.450]
Equity to assets	-1.5953	-0.6873
	[1.200]	[0.672]
Cost to income	-1.2524 **)	-1.7315 **)
	[2.295]	[2.024]
Return on equity	1.8902 ***)	4.2259 **)
Time and country fixed effects included		
Observations	520	95
Number of banks	129	95
R-squared	0.85	0.77

Source: ECB calculations.
Note: Size and ROE are orthagonalised to all other variables.
z statistics in brackets
*) significant at 10%
**) significant at 5%
***) significant at 1%

Table A.2 Drivers of tail beta: euro area sample

Constant	-0.8928
	[1.157]
Commission and fee income	1.9833 ***)
	[2.680]
Trading income	3.8990 ***)
	[3.604]
Other operating income	1.4388
	[1.034]
Net interest margin	-0.3870 ***)
	[4.745]
Loans to assets	-1.9517 ***)
	[2.648]
Size	0.7601 ***)
	[14.531]
Equity to assets	-2.9610 **)
	[2.016]
Cost to income	-1.6531 ***)
	[2.771]
Return on equity	1.4313 **)
	[2.122]
Time and country fixed effects included	
Observations	403
Number of banks	102
R-squared	0.8641

Source: ECB calculations.
Note: Size and ROE are orthagonalised to all other variables.
z statistics in brackets
*) significant at 10%
**) significant at 5%
***) significant at 1%

The table shows 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 traditional intermediation activities. The lowest of the coefficients is on the commission income share, although this is still significant at the 10% level. Larger coefficients are obtained for trading income and other operating income. Both are highly significant, and indicate that banks that are more involved in these kinds of activities have a higher tail beta. Trading revenue is the most significant contributor to having a higher tail beta.

The estimation results reveal that other indicators of bank specialisation in traditional intermediation corroborate the finding that traditional banking activities are less risky. Banks with a higher interest margin or a higher loans-to-asset ratio are perceived to be less affected by extreme market shocks, as higher values in these ratios significantly reduce banks' tail betas. Hence, banks that focus more on lending activities are less prone to systemic risk than diversified banks. However, as the balance sheet data do not include the type of lending undertaken by these banks, it is unclear whether certain types of lending reduce tail beta.

Size is by far the most significant driver of banks' tail betas. Larger banks are active in a

Table A.3 Implied changes in tail beta: full sample

	Percentage point change in tail beta
Commission and fee income	1.00
Trading income	1.22
Other operating income	0.95
Net interest margin	-2.91
Loans to assets	-1.77
Size	5.82
Equity to assets	-0.65
Cost to income	-0.95
Return on equity	0.77

Source: ECB calculations.
Note: The implied effects are reported as basis points.

variety of sectors in several countries and are more tied to European-wide shocks. Smaller banks are probably more tied to crashes in a local stock market index as they are predominantly active in their home country. Finally, the ratio of capital to assets exhibits the expected sign, but the coefficient is not significantly different from zero. This variable becomes significant for a smaller sample of euro area-only banks (see Table A.2).

The dependent variable is a probability bounded between zero and one. To recover the implied values of the dependent variable, the left-hand variable in the regression has to be transformed.[13] The effect of a change in one variable on the tail beta is shown in Table A.3. This shows the estimated impact on the tail betas if the value of any independent variable is increased by one standard deviation (and all other ratios are kept at their sample mean). The numbers shown are in basis points.

These implied changes indicate that bank size is by far the most important contributor to heterogeneity in tail risk. A bank that is one standard deviation larger than another bank will, all things being equal, have a 6% higher probability that a large drop in its equity return could occur if there is a large negative shock to the European market return index.

The implied effect of trading income is important in statistical and economic terms. A one standard deviation increase in bank income generated by trading activities increases the co-crash probability by a factor of 1.22. An identical increase in trading income has a larger effect than a parallel increase in commission income.

As expansion into non-traditional banking activities may be capital-intensive, this could be accompanied by a reduction in a bank's lending and consequently interest margins.

ROBUSTNESS CHECKS

The relationships between a bank's tail beta and averages of bank ratios (Tables A.1 and A.2) were estimated using multiple observations on the same banks over rolling eight-year time windows. One possible concern was the potential endogeneity of the relationship. The long-run relationship may have reflected the tradition that riskier banks engage in non-traditional banking activities, rather than the reverse. The equity-to-asset ratio and return on equity could also suffer from the same problem if banks' capital buffers are eroded by unexpected losses due to riskier income activity. Finally, given that the risk measure is based on stock market values, there could potentially be a spurious relationship between trading income and tail betas.

These possibilities were checked using the initial values of the ratio of each of these variables at the beginning of each eight-year period rather than the average values over the full period. For the other variables, the ratios remained eight-year averages. Trading income was still significant, which indicates that trading income causally affects bank risk. Second, return on equity had less of a significant impact. This indicates that part of the risk-return relationship can be attributed to the

13 The estimated regression takes the following form:

$\ln\left(\dfrac{p}{1-p}\right) = X\beta$. The left-hand variable in the regression has been transformed using logistic transformation.

higher profits that risky activities generate. Banks that took on more risk (as measured over an eight-year period) saw higher average profits over that period. Nevertheless, the initial profitability level was still significantly and positively related to a bank's extreme risk exposure. Finally, a bank's initial capital ratio significantly reduces its exposure to extreme systematic risk. The tail betas of financially strong banks (at the beginning of the period) are less affected by a crash in the stock market return index. However, as noted earlier, the relationship is not statistically significant.

Large and complex banking groups (LCBGs) potentially differ substantially from the other banks in the sample.[14] They could exhibit differences in terms of asset liability structure as well as revenue composition. A difference in the means test between LCBGs and the remaining banks in the sample confirmed that both differ in respect of their asset composition and revenue structure. However, a separate regression showed that this variation does not affect the relationships between the revenue variables and the co-crash probabilities, having controlled for various effects including size and capitalisation. After controlling for numerous variables (see Table A.1), a similar change in the revenue structure of an LCBG and a non-LCBG will, all things being equal, lead to a similar changes in these banks' tail betas.[15]

CONCLUDING REMARKS

This Special Feature has investigated the relationship between individual banks' income diversity and extreme risk measures – tail betas – based on equity returns data for euro area and EU15 banks. The main findings are that there is a long-run positive relationship between size, trading income, and tail betas. Size – in terms of assets – and a higher proportion of trading income in total income contribute to a higher tail beta. By contrast, there is a negative relationship between the tail beta measure and interest income and other proxies of traditional intermediation activity, indicating

that this tends to generate lower conditional probabilities.

While the present Special Feature has used conditional probabilities, further work could analyse the interaction between various income components; to understand what, if any, diversification effects exist; and whether this systematically affects accounting and stock returns measures. This would be especially useful given the dearth of work in this area for the euro area and the EU compared to that for the United States. Overall, these results confirm the necessity of analysing the underlying sources of profitability of large banking groups when assessing the stability of the euro area and EU financial system.

14 More information on how to obtain the set of LCBGs can be found in ECB (2006), "Identifying large and complex banking groups for financial system stability assessment", *Financial Stability Review*, December. Based on a multiple indicator approach, cluster analysis, it identifies 33 banking groups as LCBGs. 24 of these are located in the EU15, but not all of them are listed.

15 A dummy variable for LCBGs was used. The dummy variable was interacted with each income share. If the dummy was significant, this would have meant that this revenue type has a different impact on tail betas for LCBGs. However, none of the interacted variables were significant.