

A general approach to integrated risk management with skewed, fat-tailed risks[☆]

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Abstract

Integrated risk management for financial institutions requires an approach for aggregating risk types (market, credit, and operational) whose distributional shapes vary considerably. We construct the joint risk distribution for a typical large, internationally active bank using the method of copulas. This technique allows us to incorporate realistic marginal distributions that capture essential empirical features of these risks such as skewness and fat-tails while allowing for a rich dependence structure. We explore the impact of business mix and inter-risk correlations on total risk. We then compare the copula-based method with several conventional approaches to computing risk.

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1. Introduction

The goal of integrated risk management in a financial institution is to both measure and manage risk and capital across a diverse range of activities in the banking, securities, and insurance sectors.² This requires an approach for aggregating different risk types, and hence risk distributions—a problem found in many applications in finance including risk management and portfolio choice.

Regardless of the sectors in which a financial institution participates, all such institutions are subject to three risk types of risk: market, credit, and operational risk.³ The distributional shape of each risk type varies considerably. Market risk, for example, typically generates portfolio value distributions that are nearly symmetric and often approximated as normal. Credit and especially operational risk generate more skewed distributions because of occasional extreme losses. These losses might be due to large lending exposures in the case of credit risk, or large catastrophes such as 9/11 in the case of operational risk. For examples of market risk, see [Jorion \(2001\)](#). [Crouhy et al. \(2001\)](#) show examples of all three risk types. [Kuritzkes et al. \(2003\)](#) present stylized pictures of a very broad range of risk types that are faced by a financial conglomerate.

While some risk types, such as market risk, are more easily characterized and measured than others, such as operational risk, much less is known about the relations among the three risks. We develop an approach to combine marginal distributions in an internally consistent and realistic manner that preserves important properties of the individual risks, such as skewness and fat tails. At the same time, our methodology can be implemented when information about inter-risk dependencies is limited, as in the case in which only correlations are available.

In this paper, we use the method of copulas to directly construct the joint risk distribution for a typical large, internationally active bank engaged in commercial banking and securities underwriting activities. Market and credit risk distributions are known to be time varying, reflecting the effects of stochastic volatility. With this in mind, we estimate dynamic models for these two risks using a multivariate GARCH approach, and then combine the resulting conditional distributions with operational risk, which is taken to be unconditional. Indeed, the dynamics of the separate risks naturally carry through to the joint and total risk distribution via the copula.

Our empirical analysis uses information obtained from regulatory reports, market data, and vendor data. Banking is presently of particular interest because of the

²Virtually all of the large multinational financial institutions operating around the world today operate in at least two of these three sectors. The Joint Forum ([Joint Forum, 2001](#), p. 5) defines a financial conglomerate as “any group of companies under common control whose exclusive or predominant activities consists of providing significant services in at least two different financial sectors (banking, securities, insurance).” According to this definition, then, such institutions are financial conglomerates.

³Credit risk, the dominant risk in a commercial bank, received a formal regulatory capital charge with the first Basel Capital Accord ([BCBS, 1988](#)). Market risk capital was added with the 1996 market risk amendment ([BCBS, 1996](#)). Under the anticipated New Basel Accord ([BCBS, 2004](#)), operational risk has been added so that each of these risks now carries a regulatory capital charge.

intense policy debate surrounding the New Basel Capital Accord (BCBS, 2004), which incorporates into regulation a new risk type (operational) that has substantially different characteristics from market or credit risks. The Joint Forum (2003) shows quite clearly how banks and insurers are actively wrestling with this issue. Although here we apply our methodology to a bank, one could just as easily extend it to an insurer or, indeed, to a financial conglomerate.

Our study is the first to use publicly available, industry-wide data to perform a comprehensive analysis surrounding the set of factors or dimensions that affect total risk. Specifically, we examine the sensitivity of risk estimates to business mix, dependence structure, risk measure, and estimation method. Few papers conduct such sensitivity analysis, and those that do focus on just one or two of these dimensions. Further, none of these prior analyses provide empirically based estimates of the risk densities themselves, and studies that do model risk based on empirical data do not conduct sensitivity analysis. Moreover, the results of these studies are difficult to generalize because their data is often based on the experience of a single institution. By using a panel of quarterly data for a set of large banks, we can have more confidence that our results are indeed representative of a typical institution. In addition, by exploring the impact of business mix, we span a wide range of business activities and hence bank types.

We find that given a risk type, total risk is more sensitive to differences in business mix or risk weights than to differences in inter-risk correlations. For a policy maker or practitioner this is good news as it is far harder to estimate inter-risk correlations than to assess business mix. The results also indicate a complex relation between volatility and fat tails in determining total risk: depending on the setting, these features either offset or reinforce each other. For example, as operational exposure increases relative to market and credit exposure, total risk measured using value-at-risk (VaR) or expected shortfall (ES) first declines significantly (operational risk has lower volatility than the other two) but then flattens as the impact of fatter tails offsets the effect of lower volatility. However, as the correlation of market and credit risk with operational risk increases, both volatility and fat tails increase. The choice of copula (normal versus Student- t), which determines the level of tail dependence, has a more modest effect on total risk.

We go on to compare the copula-based method with three simpler approaches to computing risk. Because most of these alternative methods are conventional in industry practice, and in one case the method is used to calculate required regulatory capital, understanding the accuracy of these easy to implement approximations relative to the more complicated copula-based approach should therefore have broad appeal. First, an approximation that sums up the risks (e.g., VaR) of the marginal distributions significantly overestimates total risk or economic capital, which is not surprising as such a method assumes perfect inter-risk correlation. Second, assuming joint normality of the risk factors imposes tails that are thinner than the empirical estimates and significantly underestimates economic capital. However, a third “hybrid” approach, which combines marginal risks using a formula that would apply to an elliptical distribution, is surprisingly accurate.

The rest of the paper proceeds as follows. In Section 2, we present a brief overview of the related literature. We then discuss risk measurement (VaR, ES) and risk aggregation in Section 3. While most of the discussion is in terms of VaR, simply because it is presently so common, we conduct robustness checks using ES and find that all results implied by VaR hold. Section 4 provides an overview of copulas, while Section 5 focuses on the marginal risk distributions by risk type and lays out our general approach. In Section 6, we present our analytical results by examining the impact of business mix, correlations, and copula type on the joint risk distribution. Section 7 provides final comments.

2. Related literature

With the rise of risk management as a distinct discipline in banking and finance, the issue of risk aggregation has only recently become a focal point of research. Using copulas toward this end is a natural application. Embrechts et al. (1999, 2002) are among the first to introduce this methodology to the finance literature. Li (2000) provides an application to credit risk and credit derivatives. Frey and McNeil (2001) emphasize the importance of tail dependence and, by introducing copulas, generalize dependence beyond correlation.⁴ Other applications of copulas for portfolio risk measurement include Bouyé (2001), Longin and Solnik (2001), Glasserman et al. (2002), and Embrechts et al. (2003).

Studies that focus more narrowly on cross-risk aggregation for a financial institution are less common. Alexander and Pétier (2003) use a common risk factor approach to characterize the joint distribution of market and credit risk for a bank. Wang (1998) lays out a series of theoretical arguments and approaches for measuring and modeling enterprise-wide risk for an insurer facing a highly diverse set of marginal risk distributions. Ward and Lee (2002) arrive at the total distribution for a diversified insurer by using a normal copula to aggregate a diverse set of risks, some of which are computed analytically (e.g., credit risk is assumed to follow a beta distribution), and others by simulation (e.g., mortality risk for life insurance).

Dimakos and Aas (2004) estimate the joint loss distribution for a Norwegian bank that also owns a life insurance subsidiary. This study, as well as that of Ward and Lee (2002), approaches the problem of risk aggregation by considering risks pair-wise. Ward and Lee (2002) use pair-wise roll-ups with a Gaussian copula. Dimakos and Aas (2004) decompose the joint risk distribution into a set of conditional probabilities and impose sufficient conditional independence that only pair-wise dependence remains; the total risk is then just the sum of the conditional marginals (plus the unconditional credit risk, which serves as their anchor). Their simulations

⁴Poon et al. (2004) use multivariate extreme value theory instead of copulas to model tail dependence. Their technique is data intensive and requires empirical observations of joint tail events. Other applications of copulas include Rosenberg (2003), who uses a copula-related methodology for multivariate contingent claims pricing. Patton (2002) uses copulas to model exchange rate dependence while Fermanian and Scaillet (2003) analyze copula estimation and testing methods.

indicate that total risk measured using near tails (95–99%) is about 10–12% less than the sum of the individual risks. Using the far tail (99.97%), they find that total risk is often overestimated by more than 20% using the additive method. These results suggest that incorporation of diversification effects can be crucial for accurate risk aggregation, particularly in the tails.

Finally, Kuritzkes et al. (2003), hereafter KSW, make a simplifying assumption of joint normality, which allows for a closed-form solution, and use a broad set of parameters to arrive at a range of risk aggregation and diversification results for a financial conglomerate. They find somewhat smaller, but still significant, differences between total risk and the sum of the individual risks. These differences are about 15% across market, credit, and operational risk for a bank, 20–25% for insurers, and 5–15% for a bancassurance-style financial conglomerate.

3. Risk measurement and VaR

3.1. Risk measurement

Risk is simply the potential for deviation from expected results, particularly adverse deviation. Behind every risky future cash flow, earnings result, or change in value lies a probability distribution of potential results. The relative magnitude of risk could be defined by a measure of spread or dispersion in the underlying distribution, such as the standard deviation or variance. However, variance is not necessarily sufficient to provide a complete description of risk: two distributions with dramatically different shapes and differing amounts of downside risk can have the same variance.

Measures such as skewness and kurtosis can be used to quantify aspects of risk that are not adequately described by variance alone. Alternatively, one can examine the percentiles of the distribution to provide characterizations such as “99% of the time interest rates will move less than $X\%$ in one day and 1% of the time the move will be greater.” This effectively summarizes VaR, a concept we take up in more detail below.

3.2. VaR

VaR has become a standard for measuring and assessing risk. VaR is broadly defined as a quantile of the distribution of returns (or losses) of the portfolio in question. Some practitioners prefer to consider the negative of this quantile, so that higher values of VaR correspond to higher levels of risk. We use the quantile itself so that larger negative values correspond to higher levels of risk.

Formally, let Y_t be the portfolio value at time t , and define the k -period-ahead portfolio return as $r_{t+k} = \ln(Y_{t+k}) - \ln(Y_t)$. We denote the $(1-\alpha)\%$ quantile estimate at time t for a k -period-ahead return as $\text{VaR}_{t+k}(\alpha)$, so that

$$Pr(r_{t+k} < \text{VaR}_{t+k}(\alpha)) = \alpha. \quad (1)$$

Much as a sufficient statistic provides a compact representation of the characteristics of the data, so VaR is hoped to give us a similarly compact sufficient risk measure. However, Christoffersen and Diebold (2000) and Berkowitz (2001) argue that rather than focusing on just one number such as VaR, risk managers and, implicitly, regulators should focus on the whole density function of returns, perhaps by using techniques such as those laid out in Diebold et al. (1998) and Berkowitz (2001). Nonetheless, interest in a simpler summary measure continues.

Artzner et al. (1997, 1999) lay out a set of criteria necessary for what they call a “coherent” measure of risk. These criteria include homogeneity (larger positions are associated with greater risk), monotonicity (if a portfolio has systematically lower returns than another for all states of the world, its risk must be greater), subadditivity (the risk of the sum cannot be greater than the sum of the risks), and the risk-free condition (as the proportion of the portfolio invested in the risk-free asset increases, portfolio risk should decline). Importantly, unless the underlying risk factors come from an elliptical distribution (the normal belongs to this family), VaR does not satisfy the subadditivity condition. Thus, a firm could concentrate all of its tail risks in one exposure in such a way that the risk borne by that exposure appears to be just beyond the overall portfolio VaR threshold (Embrechts et al. 1999, 2002).

A related statistic, expected shortfall (ES), which is also sometimes referred to as conditional VaR, is a coherent risk measure that estimates the mean of the beyond-VaR tail region. Specifically, using Eq. (1), time- t ES for horizon k at confidence level $1-\alpha$ is defined as

$$ES_{t+k}(\alpha) = E[r_{t+k} | r_{t+k} < VaR_{t+k}(\alpha)]. \quad (2)$$

Similar to our reporting convention for VaR, we take ES to be a tail expectation of losses, so that ES is also negative. While our empirical results in Section 6.2 largely discuss the VaR method, we conduct robustness checks using ES as well.

3.3. Portfolio VaR

One of the original approaches to portfolio risk measurement is Markowitz's (1959) mean-variance analysis. Consider a simple case of three assets (or more broadly, three cash-flow generating processes) with returns r_x , r_y , and r_z and weights w_x , w_y , and w_z such that these weights sum to one. The portfolio return is simply $r_p = w_x r_x + w_y r_y + w_z r_z$ and the variance is

$$\sigma_p^2 = w_x^2 \sigma_x^2 + w_y^2 \sigma_y^2 + w_z^2 \sigma_z^2 + 2w_x w_y \sigma_{x,y} + 2w_x w_z \sigma_{x,z} + 2w_y w_z \sigma_{y,z}, \quad (3)$$

where σ_i^2 is the variance of the i th return and $\sigma_{i,j}$ is the covariance between returns i and j .

Then, assuming for simplicity that the portfolio expected return is zero, the portfolio VaR can be written as (see, for instance, Bradley and Taqqu, 2003)

$$VaR_p(\alpha) = \sigma_p F_p^{-1}(\alpha), \quad (4)$$

where $F_p^{-1}(\alpha)$ is the α th quantile of the standardized portfolio return (r_p/σ_p). Note that $F_p^{-1}(\alpha)$ is the standardized quantile function, which measures risk in terms of the

number of standard deviations from zero. Note also that $F_p^{-1}(\alpha)$ is a negative number (e.g. -3.1 for the 0.1st percentile of the standard normal distribution) and σ_p is positive; thus, $\text{VaR}_p(\alpha)$ is also negative.

By substituting portfolio volatility equation (3) into the VaR, Eq. (4), we have

$$\begin{aligned}\text{VaR}_p(\alpha) &= \sqrt{w_x^2\sigma_x^2 + w_y^2\sigma_y^2 + w_z^2\sigma_z^2 + 2w_xw_y\sigma_{x,y} + 2w_xw_z\sigma_{x,z} + 2w_yw_z\sigma_{y,z}} [F_p^{-1}(\alpha)] \\ &= \left(\sqrt{w_x^2\sigma_x^2 [F_p^{-1}(\alpha)]^2 + w_y^2\sigma_y^2 [F_p^{-1}(\alpha)]^2 + w_z^2\sigma_z^2 [F_p^{-1}(\alpha)]^2 + 2w_xw_y\sigma_{x,y} [F_p^{-1}(\alpha)]^2 + \dots} \right) \text{sign} [F_p^{-1}(\alpha)].\end{aligned}\quad (5)$$

Eq. (5) tells us that the VaR of the portfolio can be written in terms of the second moments of the marginal returns and the inverse distribution function of the standardized portfolio returns. We can think of the quantile $F_p^{-1}(\alpha)$ as providing a scaling factor for each volatility.

Now, suppose the quantiles of the individual standardized returns are the same as for the portfolio returns, i.e., $F_p^{-1}(\alpha) = F_x^{-1}(\alpha) = F_y^{-1}(\alpha) = F_z^{-1}(\alpha)$. For example, this is true for the multivariate normal distribution. Given this equality, and under the assumption that $\text{sign} [F_p^{-1}(\alpha)] = -1$ (meaning we are looking at losses), we write portfolio VaR, which we denote by H-VaR (H for hybrid), as

$$\begin{aligned}\text{H-VaR}_p(\alpha) &= -\sqrt{w_x^2\sigma_x^2 [F_x^{-1}(\alpha)]^2 + w_y^2\sigma_y^2 [F_y^{-1}(\alpha)]^2 + w_z^2\sigma_z^2 [F_z^{-1}(\alpha)]^2 + 2w_xw_y\sigma_{x,y} [F_x^{-1}(\alpha)] [F_y^{-1}(\alpha)] + \dots} \\ &= -\sqrt{w_x^2[\text{VaR}_x(\alpha)]^2 + w_y^2[\text{VaR}_y(\alpha)]^2 + w_z^2[\text{VaR}_z(\alpha)]^2 + 2w_xw_y\rho_{x,y} [\text{VaR}_x(\alpha)(\text{VaR}_y(\alpha))] + \dots}.\end{aligned}\quad (6)$$

Eq. (6) says that portfolio VaR can be computed using the same formula as portfolio volatility, where each volatility is replaced by the corresponding VaR. If we calculate H-VaR when the marginals come from different density families, then some volatilities could be overweighted and others underweighted relative to the actual VaR. The net effect will depend on the relations among the marginal quantiles, the volatilities, and the portfolio quantile. Notice, however, that H-VaR does allow the tail shape of the marginals to affect the portfolio VaR estimate.

Eq. (6) simplifies considerably when the individual returns are uncorrelated, i.e. $\sigma_{i,j} = 0 \forall i, j$, in which case we then have

$$\text{VaR}_p(\alpha) = -\sqrt{w_x^2[\text{VaR}_x(\alpha)]^2 + w_y^2[\text{VaR}_y(\alpha)]^2 + w_z^2[\text{VaR}_z(\alpha)]^2}.$$

When the risks are perfectly correlated ($\rho_{i,j} = 1 \forall i, j$), Eq. (6) becomes (for positive weights)

$$\text{Add-VaR}_p(\alpha) = w_x \text{VaR}_x(\alpha) + w_y \text{VaR}_y(\alpha) + w_z \text{VaR}_z(\alpha). \quad (7)$$

We refer to this as additive VaR or Add-VaR. When risk correlations are less than one, we expect Add-VaR to overestimate risk. Like H-VaR, Add-VaR allows the tail shape of the marginals to affect the portfolio VaR estimate.⁵

Another special case of Eq. (5) is obtained by assuming that the risk distribution is multivariate normal, which makes it also a special case of Eq. (6). Then, each of the marginals is normal, and Normal VaR (N-VaR) has standardized quantiles given by the inverse standard normal distribution function ($\Phi^{-1}(\alpha)$):

$$\text{N-VaR}_p(\alpha) = -\sqrt{w_x^2\sigma_x^2\Phi^{-1}(\alpha)^2 + w_y^2\sigma_y^2\Phi^{-1}(\alpha)^2 + w_z^2\sigma_z^2\Phi^{-1}(\alpha)^2 + 2w_xw_y\sigma_{x,y}\Phi^{-1}(\alpha)^2 + \dots} \quad (8)$$

It is clear that N-VaR is accurate only when the joint risk distribution is multivariate normal. N-VaR is most likely to fail when one or more marginals exhibit significant negative skewness or excess kurtosis. In that case, the normal quantile underestimates the actual marginal quantile.

Clearly, the closeness of each of the VaR approximations (hybrid, additive, and normal) to the actual VaR will depend on the validity of their underlying assumptions. H-VaR has the least restrictive assumptions, since it permits the correlations and marginal quantiles to depend on the data. Add-VaR restricts the correlations to unity, but does not restrict the quantiles. N-VaR forces the quantiles to come from a normal distribution but allows the correlations to be estimated from the data.

Each of these approximations relies on the assumption that the quantiles of the portfolio are the same as those of the marginals. When $F_p^{-1}(\alpha) \neq F_x^{-1}(\alpha) \neq F_y^{-1}(\alpha) \neq F_z^{-1}(\alpha)$, we are left with the problem of computing Eq. (5) when F_p^{-1} is unknown. To obtain the correct portfolio VaR, we therefore need to obtain the joint return distribution of the portfolio. Copulas allow us to solve this problem by combining the specified marginal distributions with a dependence function to create this joint distribution. The joint distribution can then be used to calculate the quantiles of the portfolio return distribution, since the portfolio returns are weighted averages of the individual returns.

4. Copulas

Copulas provide important theoretical insights and practical applications in multivariate modeling; an excellent reference is Nelsen (1999). The essential idea of the copula approach is that a joint distribution can be factored into the marginals and a dependence function called a copula. The term copula is based on the notion of “coupling”: the copula couples the marginal distributions together to form a joint distribution. The dependence relationship is entirely determined by the copula, while

⁵Note that Add-VaR assumes an elliptical underlying distribution and perfect correlation. If the actual distributions are not members of this family, then Add-VaR might not provide an upper bound for VaR. This would be an example of the failure of subadditivity.

location, scaling and shape (e.g., mean, standard deviation, skewness, and kurtosis) are entirely determined by the marginals.

Using a copula, marginal risks that are initially estimated separately can then be combined in a joint risk distribution that preserves the original characteristics of the marginals. This is sometimes referred to as obtaining a joint density with pre-determined marginals. For example, when individual risk distributions are estimated using heterogeneous dynamic models that cannot be easily combined into a single dynamic model (e.g., different explanatory variables, different variable frequencies, or different model types), the marginals can be thought of as pre-determined. The copula approach is then naturally applied to combine these time-varying marginal risk distributions to obtain a time-varying joint risk distribution.

In addition, there are cases in which marginal risks are not estimated using time-series data (e.g., implied density estimation, survey data, or the combination of frequency and severity data). There is then no direct way to create a multivariate dynamic model that incorporates all of the risk types. Once again, the copula method can incorporate these marginal risks into a joint risk distribution.

The copula approach is also useful when “off-the-shelf” multivariate densities inadequately characterize the joint risk distribution. In the risk management context, the multivariate normal distribution is known to poorly fit the skewed, fat-tailed properties of market, credit, and operational risk. Using a copula, parametric or nonparametric marginals with quite different tail shapes can be combined into a joint risk distribution. Joint risk distributions created using copulas can also span a range of dependence types beyond correlation such as tail dependence.

4.1. Representation of a joint distribution using a copula

One of the fundamental results concerning copulas is known as Sklar’s Theorem. This theorem states that any joint distribution can be written in terms of a copula and marginal distribution functions. This representation shows that it is possible to separately specify each variable’s marginal distribution and the dependence relation that links these marginals into a joint distribution. The standard representation for the joint distribution $F_{x,y}$ is

$$F_{x,y}(x,y) = C(F_x(x), F_y(y)), \quad (9)$$

where $C(u,v)$ is the copula, and F_x as well as F_y are the cumulative marginal distribution functions.

Alternatively, there is the density representation

$$f_{x,y}(x,y) = f_x(x)f_y(y)c(F_x(x), F_y(y)), \quad (10)$$

where $c(u,v) = (\partial^2 / \partial u \partial v)C(u,v)$ is the copula density, and f_x as well as f_y are the marginal density functions.

In Eq. (9), the marginal information is embedded in $F_x(x)$ and $F_y(y)$, and the dependence information is captured by $C(u,v)$. The copula itself is a joint distribution with uniform marginals, so it maps points on the unit square $(u,v) \in [0,1] \times [0,1]$ to values between zero and one. The copula relates the quantiles of the two

distributions rather than the original variables, so that the copula for two random variables is unaffected by a monotonically increasing transformation of the variables. For example, the copula of the joint distribution of X and Y is the same as the copula of the joint distribution of $\ln(X)$ and $\exp(Y)$.

4.2. Constructing a joint distribution using a copula

The copula for any multivariate distribution function can be obtained using *the method of inversion*. This technique factors out the effects of the marginal distributions on the dependence relation by substituting the arguments of the original joint distribution with the marginal quantile functions. Using this method, the copula $C(u, v)$ of the joint distribution $F_{x,y}$ is

$$C(u, v) = F_{x,y}(F_x^{-1}(u), F_y^{-1}(v)), \quad (11)$$

where F_x^{-1} and F_y^{-1} are the marginal quantile functions, and u as well as v are probabilities.

For example, we can determine the normal copula using the method of inversion. If $\Phi(x, y; \rho)$ is a bivariate standard normal cumulative distribution function and $\Phi^{-1}(u)$ and $\Phi^{-1}(v)$ are standard normal quantile functions, then the normal copula is simply $\Phi(\Phi^{-1}(u), \Phi^{-1}(v); \rho)$. The bivariate normal copula has a single parameter, the correlation coefficient ρ .

A joint distribution with given marginals and a given copula can be created by plugging the marginal distributions into the copula function. To obtain the joint distribution $F_{a,b}$ using the copula $C(u, v)$ and the marginals F_a and F_b , we have

$$F_{a,b}(a, b) = C(F_a(a), F_b(b)). \quad (12)$$

So, to create a bivariate distribution with given marginals and a *normal* copula, one simply inserts the marginal distributions into the normal copula as $\Phi(F_x^{-1}(u), F_y^{-1}(v); \rho)$. It is worth noting that the correlation between the risks is not necessarily equal to ρ . The non-normality of the marginal densities drives a wedge between the ρ and the Pearson correlation coefficient. In addition, it is possible that some correlations cannot be attained for certain choices of marginals.

4.3. Simulation using copula-based multivariate densities

Techniques for simulating realizations from the multivariate standard normal distribution are well-known. One common approach is to first draw uncorrelated univariate standard normal vectors. These are transformed into correlated draws from a multivariate standard normal distribution using a Cholesky factorization of the correlation matrix.

A related approach can be used to simulate realizations from a multivariate distribution written in terms of a copula and marginal distributions. For clarity, we illustrate how to simulate random variables A and B from a joint distribution

generated using a bivariate normal copula and given marginals (F_x and F_y). Notice that F_x and F_y can be defined either parametrically or non-parametrically.

First, two uncorrelated standard normal vectors are generated and transformed to correlated standard normal vectors using the lower triangular Cholesky factor.⁶ Then, we have $X, Y \sim \Phi(x, y; \rho)$. We transform X and Y into realizations from a normal copula by applying the normal cumulative distribution function to each vector [$U = \Phi(X)$, $V = \Phi(Y)$] so that $U, V \sim \Phi(\Phi^{-1}(u), \Phi^{-1}(v); \rho)$. Finally, we obtain A and B by applying the inverse cumulative distribution function for each marginal to U and V [$A = F_x^{-1}(U)$, $B = F_y^{-1}(V)$].

5. Marginal risk distributions: market, credit, and operational

In this section, we consider the problem of modeling the marginal risk distributions for a typical large, internationally active bank. This is the kind of bank that regulators have in mind when designing capital regulation (BCBS, 2004). As noted earlier, we focus on three risk-types, namely market, credit, and operational. Market risk measures the risk of adverse movements in market factors such as asset prices, foreign exchange rates, or interest rates. The risk of loss resulting from failure of obligors to honor their payments is referred to as credit risk, while operational risk can be defined as (BCBS, 2004, §644) “the risk of loss resulting from inadequate or failed internal processes, people, and systems, or from external events.” This list is hardly exhaustive; for instance, mortality and morbidity risk is typically incurred by life insurers but rarely by banks. Nonetheless, any financial institution is subject to these three risk types and hence they form the focus of our study.

While all banks are subject to minimum capital standards due to credit risk, only banks with a *significant* market risk exposure are required to calculate a risk-based capital ratio that takes into account market risk in addition to credit risk. U.S. regulators deem market risk exposure to be significant if the gross sum of trading assets and liabilities on the bank’s balance sheet exceeds 10% of total assets or \$ 1 billion (USGAO, 1998, p. 121). As reported in Hirtle (2003, Table 1), at the end of 2001 there were 19 bank holding companies (BHCs) that were subject to market risk capital standards. This set of institutions forms the sample of banks for our analysis. As a benchmark, we consider the risk and business activity profile of the median bank from the subset for which we have complete data; there are 17 such banks.

⁶If the two uncorrelated standard normal random variables are Z_1 and Z_2 , then $X = Z_1$ and $Y = \rho Z_1 + \sqrt{(1 - \rho^2)} Z_2$. This method is easily extended to simulate Student- t variates with ν degrees of freedom. The Student- t realization is obtained by multiplying each normal pair (X_i, Y_i) by $\sqrt{\nu/s_i}$, where s_i is drawn from a chi-square distribution with ν degrees of freedom. Then, the inverse cumulative distribution function for a Student- $t(\nu)$ is applied instead of the inverse normal to create a Student- t copula realization.

Table 1
Summary table for 17 bank holding companies (BHCs) in the sample

Bank holding company	Total assets	Lending assets	Trading assets	Percent lending assets (%)	Percent other assets (%)	Net income	Net interest income	Provisions	Trading revenue	Minimum market risk capital requirement	Market risk share of capital requirement (%)	Return on assets (%)
ABN Amro N. America	139,605	61,343	3,106	43.9	53.8	434	2,349	145	147	121	0.16	0.31
Bank of America	660,458	356,451	95,829	54.0	31.5	9,249	20,210	1,165	778	2,313	0.44	1.40
Bank One	277,383	148,125	11,000	53.4	42.6	3,295	8,569	628	224	140	0.06	1.19
Citigroup	1,097,190	477,323	155,208	43.5	42.3	15,276	37,882	2,690	4,513	2,446	0.35	1.39
FleetBoston Financial	190,589	119,427	4,486	62.7	35.0	1,188	6,369	813	584	251	0.14	0.62
HSBC N. America	113,371	59,649	14,592	52.6	34.5	860	2,813	42	96	172	0.24	0.76
J.P. Morgan Chase	758,800	216,253	248,301	28.5	38.8	1,663	11,526	921	2,594	2,663	0.58	0.22
Keycorp	84,710	62,457	2,561	73.7	23.2	979	2,762	147	65	15	0.02	1.16
Mellon Financial	36,306	8,420	1,911	23.2	71.5	682	697	6	183	60	0.23	1.88
PNC	66,410	37,089	926	55.8	42.8	1,184	2,198	65	95	16	0.03	1.78
State Street	85,794	5,128	3,435	6.0	90.0	1,015	979	1	259	27	0.10	1.18
Suntrust Banks	117,323	80,916	1,718	69.0	29.6	1,332	3,244	97	120	20	0.02	1.14
Deutsche Bank (Taurus)	224,278	16,843	64,270	7.5	63.8	-2,109	1,029	97	-165	243	0.00	-0.94
Bank of New York	77,576	32,015	7,309	41.3	49.3	902	1,739	93	234	43	0.06	1.16
U.S. Bancorp	180,027	120,410	898	66.9	32.6	3,289	6,840	349	227	47	0.03	1.83
Wachovia	341,839	171,801	33,155	50.3	40.0	3,579	10,021	308	24	505	0.19	1.05
Wells Fargo	349,259	254,453	10,167	72.9	24.2	5,435	14,858	438	321	374	0.13	1.56
Mean	277,241	127,009	37,591	48	44	2,839	7,887	456	606	559	0.18	1.07
Median	177,941	76,343	8,131	53	39	1,188	3,244	195	224	168	0.14	1.19

Units are millions U.S. dollars, year-end 2002. Stocks (e.g., assets) are year-end, flows (e.g., net income) are the sum of four quarters. Means and medians are taken over the four quarters. The data source is Y-9C BHC regulatory reports.

5.1. *The bank sample*

We have quarterly data for 17 BHCs from 1994Q1 to 2002Q4, obtained from Y-9C regulatory reports expressed on a pro-forma basis that go back in time to account for mergers. See Table 1 for details. For example, if a bank in 2002 is the result of a merger in 2000, pre-2000 data is merged on a pro-forma basis. We use this data to arrive at typical size and business mix characteristics. Thus, for the last year of the sample period the average (median) BHC has \$277bn (\$178bn) in assets, 48% (53%) of which is devoted to lending. Even though only these banks were required to report market risk, the market risk share of the minimum capital requirement is rather small on average (median): 0.18% (0.14%).⁷ The average (median) return on assets was 1.07% (1.19%). Because the size distribution of banks is quite skewed—there are a few very large banks—we use medians to characterize the typical bank.

5.2. *General approach*

In developing a modeling framework for the joint risk distribution of a bank, we face a number of challenges. First, there is the range of business mix. The “typical” bank we have in mind is engaged in a range of business activities, some of which are more intensive in market risk (like trading), credit risk (like lending), or operational risk (like custody).

A second important consideration is the units in which the risk type is measured and reported. To arrive at an aggregate risk distribution, we need a common currency of risk. Market risk is typically based on the return distribution of the end-of-day positions in the trading book. Similarly, credit risk can be described by a loss or return distribution, typically in terms of percentage exposure. In both cases we need to know the exposure at risk, e.g., trading or lending assets, to compute dollars at risk.

Finally, operational risk is not yet part of the regulatory framework—but will be under the New Basel Accord—so typically banks do not currently report operational risk. Data for this risk type is only recently becoming available, and we rely on external sources to characterize and calibrate our operational risk distribution. The measurement unit for this risk type is in dollars. We convert the operational risk losses into a “return” by normalizing with respect to total assets, since all assets and activities of the bank are in some way subject to this risk type.

The overall or total risk distribution will simply be a weighted combination of the individual risks, where the weights, which add up to one, are determined by the risk-specific exposures. We determine exposures and risk weights as follows. Market risk exposure is equal to trading assets, credit risk exposure is equal to lending assets, and operational risk exposure is equal to total assets. We call the sum of these three exposures the “total book,” and each risk weight is simply the ratio of the exposure

⁷This small amount of market risk regulatory capital is not necessarily inconsistent with industry benchmarks of economic capital arising from internal models, which are closer to 20%. Only position risk, i.e., risk arising from trading activities, is measured for purposes of assigning regulatory capital. Interest rate risk due to asset liability mismatch (ALM) is typically included in internal models.

to the total book. Based on BHC characteristics at the end of 2002, the risk weights for our benchmark bank are 3.1%, 29.1%, and 67.8% for market, credit, and operational risk. To be sure, these weights could be somewhat arbitrary because they only include on-balance sheet items.⁸ Although off-balance sheet items can be larger, this is the usual treatment. We do not consider these weights as benchmarks per se but rather as a useful starting point from which to conduct our business mix experiments. After all, we are interested in understanding the range of total risk outcomes as the business mix changes.

Our ex ante weights are quite different from the ex post risk contribution from business lines discussed in other studies.⁹ For example, KSW report that the average ex post decomposition based on bank internal models attributes about 20% of economic capital to market risk, 55% to credit risk, and 25% to operational risk. When we perform an ex post risk decomposition using our ex ante benchmark risk weights (Section 6.2), we obtain generally similar results.

For market and credit risk, we model the return due to each risk type as a function of observable risk factors. This approach allows us to separately measure factor sensitivities and model risk factor dynamics. We then estimate marginal risk distributions by combining the time-varying risk factor distributions with the factor sensitivities.¹⁰ For operational risk, it is far from clear which observable risk factors might drive operational risk. Thus, we work with the unconditional distribution, the details of which are provided below in Section 5.6.

We proceed by letting bank i returns from risk type $j = \{\text{market, credit}\}$ at time t be driven by a set of observable risk factors $\mathbf{x}_{j,t}$, as given by

$$r_{i,j,t} = \alpha_{i,j} + \beta'_{i,j} \mathbf{x}_{j,t} + \varepsilon_{i,j,t}. \quad (13)$$

In Eq. (13), bank returns attributable to risk type j are said to be captured by the set of observable risk factors collected in $\mathbf{x}_{j,t}$. We estimate factor sensitivities using panel data, so these are perhaps best interpreted as time averaged if actual sensitivities are time varying. The risk factors are themselves subject to complex dynamics that are specified and estimated separately.

Naturally, our chosen factors ($\mathbf{x}_{j,t}$) do not necessarily capture all of the relevant risks. However, as long as the omitted factors that appear in $\varepsilon_{i,j,t}$ are not correlated with observable factors, we suffer only loss of efficiency but no bias in estimating the bank-specific set of factor sensitivities $\beta'_{i,j}$. To be sure, some residual market and

⁸This was kindly pointed out by a referee.

⁹The difference arises primarily because the ex post contribution depends on both the exposure and the riskiness of the business line, while the ex ante weight is only a function of the exposure. For instance, all business activities are exposed to some operational risk (high ex ante weight), but this need not result in a large attribution to operational risk capital (ex post contribution) if operational activities have relatively low risk. A useful analogy is the example of a portfolio invested in a low risk and a high risk asset, e.g., US treasuries and the S&P500. One could place a majority of the portfolio in the former (high ex ante weight) but still have the overall portfolio risk be driven largely by the latter (high ex post risk contribution).

¹⁰An example of this approach for market and credit (but not operational) risk is Alexander and Pézier (2003). See also Jorion (2002) for the importance of market exposures of trading revenues on reported market risk.

credit risk might be captured by our operational risk measure, but a significant amount of the unexplained variation is likely to be bank specific. We analyze residual risk in Section 5.4.

An advantage of proceeding along the lines of Eq. (13) is that the time series available for bank data, $r_{i,j,t}$, is much shorter and is at a lower frequency (quarterly from 1994 to 2002) than what is available for the risk factors $\mathbf{x}_{j,t}$ (daily from 1974 to 2002 for the market risk factors and monthly from 1988 to 2002 for the credit risk factors). Using the factor approach, we can construct the marginal risk distributions from a much richer history of risk factor movements than what we have observed at a quarterly frequency in the last nine years.

The income from market risk-related activities is captured in the regulatory reports as “Trading Revenue.” While fluctuations from this income source include the outcomes of position taking, arguably some of this revenue comes from customer-related activities such as fees and commissions. Regulatory reporting, however, focuses on sensitivity of the trading book to risk factors such as equity returns, interest rates, and foreign exchange rates. We therefore direct our analysis by regressing trading returns, defined as trading revenue over trading assets, on returns and volatilities of risk factors from a broad set of asset classes in the capital markets: equities, currencies, and government bonds.

Most credit risk arises from lending, which generates fees and interest income. The former is not separately reported, so we proxy total credit risk-related income by net interest income less a charge for incurred losses as proxied by provisions. To define a credit return, we divide this net credit income by the lending assets. In thinking about modeling the variation in this return, credit spreads come immediately to mind as they should yield the appropriate filtering over a wide set of factors, such as default risk, that we would expect to drive the profits and losses of a bank’s loan portfolio.

Having defined the dependent variable in Eq. (13) for market and credit risk, we specify the factor dynamics.

5.3. *Specification of risk factor dynamics*

It is well known that asset returns exhibit stochastic volatility, which can create skewness and kurtosis in the resulting risk distributions. To capture this phenomenon, we estimate the joint distribution of the factor risks within a multivariate GARCH framework. In particular, we estimate the asymmetric BEKK model proposed by Kroner and Ng (1998) that allows for different volatility impacts of positive and negative shocks. Asymmetric volatility effects can be important to capture, for example, the negative skewness in equity returns or the positive skewness in changes in credit spreads. This model can be written as

$$\begin{aligned} \mathbf{r}_t &= \boldsymbol{\mu} + \boldsymbol{\alpha}\mathbf{r}_{t-1} + \boldsymbol{\varepsilon}_t, \quad \boldsymbol{\varepsilon}_t | \boldsymbol{\Xi}_{t-1} \sim \mathbf{N}(\mathbf{0}, \mathbf{H}_t), \\ \mathbf{H}_t &= \boldsymbol{\Omega} + \mathbf{A}'\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}'\mathbf{A} + \mathbf{B}'\mathbf{H}_{t-1}\mathbf{B} + \mathbf{G}'\boldsymbol{\eta}_{t-1}\boldsymbol{\eta}_{t-1}'\mathbf{G}. \end{aligned} \quad (14)$$

The first equation in Eq. (14) models the expected return dynamics of the $n \times 1$ vector of risk factors (\mathbf{r}_t), with a vector of constants ($\boldsymbol{\mu}$) and a first-order

autoregressive component with parameter (α). The second equation in Eq. (14) models the volatility dynamics of the factor innovations ε_t , conditional on the information set Ξ_t , where \mathbf{H}_t is the $n \times n$ conditional covariance matrix of the n factors.

Conditional variances depends on a constant parameter matrix (Ω), scaled lagged squared innovations ($\varepsilon_{t-1}\varepsilon'_{t-1}$), the lagged covariance matrix (\mathbf{H}_{t-1}), and a matrix of asymmetric terms ($\boldsymbol{\eta}_{t-1}\boldsymbol{\eta}'_{t-1}$), where $\eta_{it} = \text{Max}[0, -\varepsilon_{it}]$ or $\text{Max}[0, \varepsilon_{it}]$. Matrices \mathbf{A} , \mathbf{B} , and \mathbf{G} are $n \times n$ lower triangular parameter matrices that provide the weights on the lagged squared innovations, lagged covariances, and asymmetric terms. Estimation is performed using maximum likelihood under the assumption of a Gaussian error density. This procedure has a quasi-maximum likelihood interpretation (Bollerslev and Wooldridge, 1992) and produces consistent parameter estimates under other error distributions.

One of the well known difficulties associated with multivariate GARCH model estimation is the large number of parameters to be estimated. Therefore, we make use of a more parsimonious version of the asymmetric BEKK model in which the \mathbf{A} , \mathbf{B} , and \mathbf{G} matrices are constrained to be diagonal. To further reduce the number of parameters required for the market risk model, we implement variance targeting (Engle and Mezrich, 1996). This procedure sets the long-run covariance from the model equal to the sample covariance matrix by imposing the restriction that $\Omega = (\mathbf{I} - \mathbf{A} - \mathbf{B})\mathbf{S}$, where \mathbf{S} is the sample covariance matrix.

Our market risk model is based on three daily risk factors from 1 January 1974 to 31 December 2002, namely equity returns, currency returns, and interest rate changes. The equity return is the log of the S&P500 return from Datastream. The interest rate measure is the log-difference of the 10-year Constant Maturity Treasury rate from the Board of Governors H.15 release. The currency return is the log difference of the trade-weighted currency index from the Board of Governors G.5 release.

For credit risk, we would like broad coverage of the credit spectrum. Thus, we use monthly changes in double-A (AA) and triple-B (BBB) credit spreads, for which we have data coverage from December 1988 to the end of 2002. We use monthly changes in AA and BBB credit spreads from Bloomberg. The spreads are constructed using the yield-to-maturity from the Merrill Lynch AA and BBB-rated corporate bond indices subtracted from duration-matched Treasury yields from the Federal Reserve Board H.15 release.

We find evidence of stochastic volatility in the market and credit risk factors. As shown in Table 2, squared market factors are predictable as evidenced by Ljung-Box statistics significant at the 1% level. Squared credit factors are also predictable with Ljung-Box test p -values of 3% and 10%. We test each factor for an asymmetric volatility effect using a univariate asymmetric GARCH specification. We find that the term $\text{Max}[0, -\varepsilon_{it}]$ is significant for equities, and $\text{Max}[0, \varepsilon_{it}]$ is significant for both credit spreads. These terms are included in the estimation of the final model.

Overall, the estimated multivariate GARCH model fits the data well. When we apply Ljung-Box tests to squared standardized model residuals, we find insignificant

Table 2
Estimated asymmetric multivariate GARCH risk factor models

	Market risk factor model			Credit risk factor model		
	Parameter estimate	Standard error	p-Value	Parameter estimate	Standard error	p-Value
μ_1	2.51E-04	1.07E-04	0.0188	0.5300	1.0357	0.6089
μ_2	2.52E-05	3.80E-05	0.5067	1.6946	1.3182	0.1986
μ_3	1.73E-05	8.87E-05	0.8456			
α_1	0.0819	0.0130	<0.001	0.2420	0.0634	<0.001
α_2	0.0495	0.0118	<0.001	0.3086	0.0948	0.0011
α_3	0.0970	0.0119	<0.001			
ω_{11}	1.12E-06			2.7851	0.5576	<0.001
ω_{22}	3.89E-08			1.9908	0.4310	<0.001
ω_{33}	4.34E-07					
ω_{21}	2.20E-08			-0.0069	34.1960	0.9998
ω_{31}	-3.00E-07					
ω_{32}	1.37E-08					
a_1	0.1830	0.0075	<0.001	0.1563	0.1603	0.3295
a_2	0.1760	0.0038	<0.001	0.0787	0.1922	0.6823
a_3	0.2217	0.0050	<0.001			
b_1	0.9635	0.0013	<0.001	0.8630	0.0449	<0.001
b_2	0.9831	0.0007	<0.001	0.9117	0.0246	<0.001
b_3	0.9725	0.0013	<0.001			
g_1	0.2367	0.0047	<0.001	0.6818	0.1187	<0.001
g_2				0.7266	0.0857	<0.001
Number of observations (log-likelihood)			7199 (78621)	169 (-1141)		
Eq. (1): Ljung-Box p-value (squared returns)			<0.001	0.030		
Eq. (2): Ljung-Box p-value (squared returns)			<0.001	0.101		
Eq. (3): Ljung-Box p-value (squared returns)			<0.001			
Eq. (1): Ljung-Box p-value (squared standardized residuals)			0.953	0.842		
Eq. (2): Ljung-Box p-value (squared standardized residuals)			0.048	0.949		
Eq. (3): Ljung-Box p-value (squared standardized residuals)			0.532			

We estimate a diagonalized asymmetric multivariate GARCH model (Kroner and Ng, 1998) for market and credit risk factors using the method of maximum likelihood. For the market risk factor model, Eq. (1) is for equity returns, Eq. (2) is for currency returns, and Eq. (3) is for log-differenced interest rates. This model is specified using variance targeting, so standard errors are not computed for the parameters of the omega matrix, which are functions of sample covariances and volatility model parameters. For the credit risk factor model, Eq. (1) is for AA credit spreads and Eq. (2) is for BBB credit spreads. Data definitions are given in Section 5.3. Note that the volatility parameters ω , a , b , g correspond to the square root of the corresponding parameters in a univariate GARCH model. Ljung-Box p -values are reported for 20 lags in the market model and three lags in the credit model for squared returns and standardized squared returns ($\varepsilon_t/\sqrt{h_t}$) using estimated conditional volatilities.

$$\begin{aligned} \mathbf{r}_t &= \boldsymbol{\mu} + \boldsymbol{\alpha} \mathbf{r}_{t-1} + \boldsymbol{\varepsilon}_t, \quad \boldsymbol{\varepsilon}_t | \Xi_{t-1} \sim \mathbf{N}(\mathbf{0}, \mathbf{H}_t), \\ \mathbf{H}_t &= \boldsymbol{\Omega} + \mathbf{A}' \boldsymbol{\varepsilon}_{t-1} \boldsymbol{\varepsilon}_{t-1}' \mathbf{A} + \mathbf{B}' \mathbf{H}_{t-1} \mathbf{B} + \mathbf{G}' \boldsymbol{\eta}_{t-1} \boldsymbol{\eta}_{t-1}' \mathbf{G}. \end{aligned}$$

p -values at the 10% level for all but one risk factor. In Fig. 1, we graph the conditional volatility and conditional correlations of the risk factors. We see that factor volatility is quite variable over the sample period. There are notable volatility

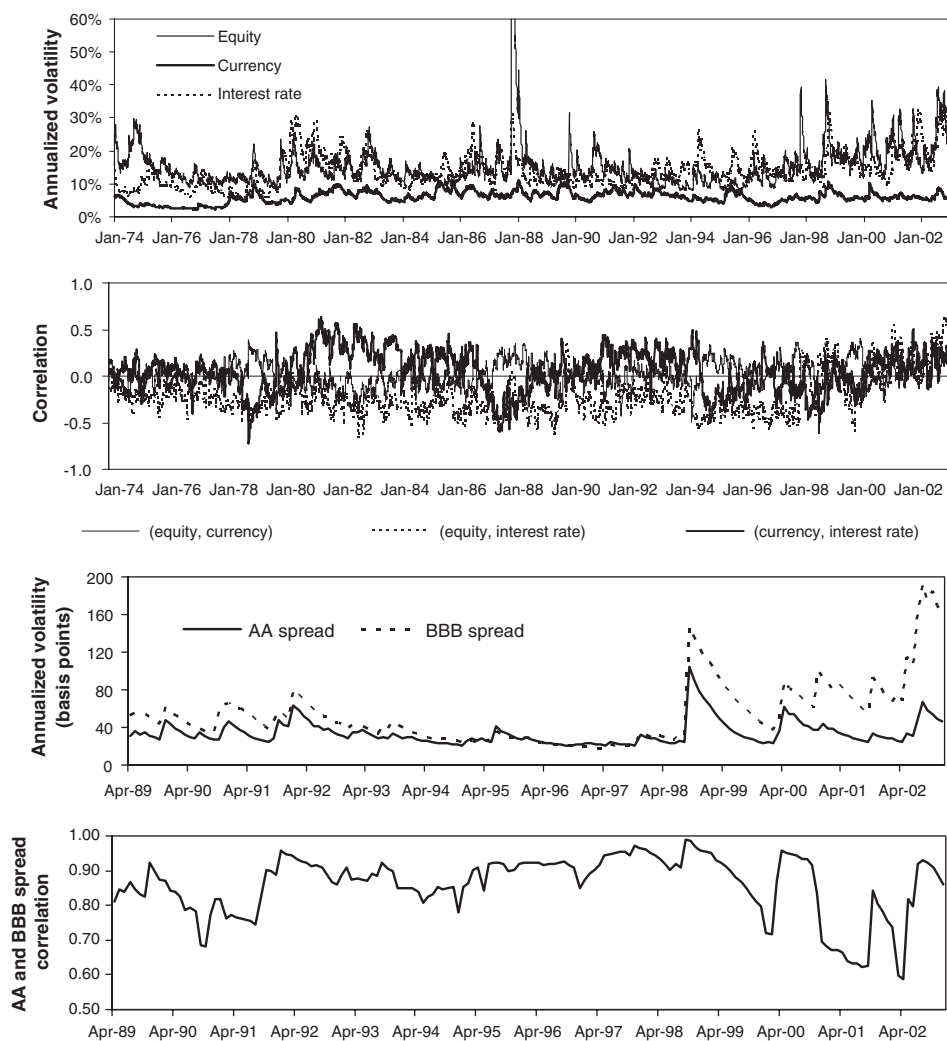


Fig. 1. Conditional volatilities and correlations from estimated multivariate GARCH model (Table 2). Top two panels plot market risk factor volatilities and correlations over the period 1974–2002. Bottom two panels plot credit risk factor volatilities and correlations over the period 1989–2002. Data definitions are given in Section 5.3.

spikes for equities in October 1997 (Black Monday, first panel) and for credit spreads in September 1998 (Russian ruble devaluation and Long Term Capital Management recapitalization, third panel). Conditional correlations for equities versus interest rates range from -0.66 to 0.64 (second panel) while conditional correlations for double-A (AA) versus triple-B (BBB) spreads range from 0.59 to 0.99 (fourth panel).

5.4. Market and credit risk

With the risk factor dynamics in hand, we estimate market and credit factor sensitivities in Eq. (13) over the sample period 1994Q1–2002Q4. We test both the factors and the factor volatilities as explanatory variables in our market and credit factor sensitivity regressions. The volatilities used in the regression are quarterly conditional volatilities from the estimated multivariate GARCH models. In the credit regressions, we find that the credit spread volatilities are not statistically significant additions to the credit spreads, so they are omitted from the final model.

Our aim is to characterize the factor sensitivities of a typical BHC. Although sensitivities vary across banks and over time, we do expect to find certain key commonalities. For example, on average, trading returns are likely to be positively related with the equity index, and credit returns are likely to be negatively related to credit spreads. For certain factors, it could be the case that some banks have large positive sensitivities and others have large negative sensitivities. In that case, our average estimate would be close to zero, which would not be representative of any of the banks. We conduct several additional tests and do not find evidence for bimodality of the factor sensitivities from the bank-level regressions.

We use median asset shares to characterize a typical large BHC for our benchmark risk weights. However, to obtain representative factor sensitivities, the median approach is not as appealing. Using the factor sensitivities of the median-sized bank would make inefficient use of the 612 bank-quarters we have in our pooled sample. Moreover, using the median sensitivity from each of the 17 bank-specific regressions would not account for correlations between the parameters. Therefore, this method might misestimate the characteristics of the typical bank.

In light of these issues, we deem that it is most reasonable to follow a pooled ordinary least squares (OLS) regression approach. In Table 3, we present estimates from this regression including bank fixed effects. We also present \bar{R}^2 for the pooled regressions with fixed effects alone and in combination with the factors, as well as the average \bar{R}^2 from the 17 bank-level regressions.

For the bank-level regressions, the market risk factors explain on average about 10% of the variation of returns (as measured by average \bar{R}^2) attributable to market risk-related activities. In the pooled regression, the addition of the risk factors increases the \bar{R}^2 from 58.3% to 59.7%. We find that the signs of the pooled regression coefficients are broadly in line with our expectations. Specifically, trading returns are positively associated with equity returns as might be expected when equity trading positions are generally net long. Trading returns are also positively related to equity volatility. This result could be due to a positive correlation between commission-based trading revenue, trading volume, and volatility. Trading returns are negatively associated with currency volatility. This would be consistent with bank exposure to volatility risk from writing foreign exchange options.

The interest rate and interest rate volatility factors are not statistically significant in the pooled regression, but the signs of the coefficients are as expected. A decline in short-term interest rates has a positive effect on returns, which would be consistent with slight positive duration. Moreover, interest rate volatility is negatively related to

Table 3
Market risk regression

Variable	Parameter estimate ($\hat{\beta}$)	Standard error	p-Value
Equity return	0.0204	0.0058	0.0005
Equity volatility	0.0122	0.0033	0.0002
Δ interest rate	−0.0056	0.0042	0.1896
Interest rate volatility	−0.0030	0.0052	0.5591
Currency return	−0.0048	0.0148	0.7442
Currency volatility	−0.0113	0.0052	0.0302
\bar{R}^2 fixed effects only	58.3%		
\bar{R}^2 fixed effects and factors	59.7%		
Average \bar{R}^2 from bank-level regressions	10.2%		
Number of observations	612		

Estimates of market risk regressions using pooled OLS with bank fixed effects. Dependent variable is annualized trading revenue divided by trading assets. Data is from Y-9C bank holding company regulatory reports over the period 1994Q1–2002Q4 using the bank holding company sample discussed in Section 5.1. Equity return is the annualized log-return of the S&P500 from Datastream. Δ interest rate is the change in the 10-year Constant Maturity Treasury (CMT) rate from the Federal Reserve Board H.15 release. Currency return is the annualized log difference of the trade-weighted currency index from the Federal Reserve Board G.5 release. Equity, interest rate, and currency volatilities are the log of daily variances from the trivariate GARCH model (Table 2) summed over the quarter and then scaled to annual terms.

trading returns, which could reflect exposure from writing interest rate options or holding long positions in assets with negative convexity such as mortgages.

Turning now to the credit risk regression, we see in Table 4 that the two credit risk factors explain on average about 5% of the variation in credit risk earnings (as measured by average \bar{R}^2) across the 17 bank-level regressions. Adding the risk factors to the pooled regression with fixed effects increases the \bar{R}^2 from 56.2% to 56.8%. As spreads on high credit quality (double-A) firms widen, returns attributable to credit activities increase. The opposite is true for spread changes for lower quality (triple-B) firms. This seems reasonable as bank lending portfolios are relatively more concentrated toward the middle and lower ends of the credit spectrum. Thus, when the credit quality of those firms deteriorates, returns attributable to bank lending activities should decline.

One reason why the lending portfolio of banks is skewed in this way is due to differential borrower access to capital markets as an alternative source of funding. Large corporates, which tend to have better credit ratings, are able to go to the capital markets instead of banks for funding. This alternative is less available to smaller, lower credit quality firms. As the cost of funding increases, i.e., the spread on high credit quality bonds widens, bank loans become more attractive as a capital source.

In addition, changes in credit spreads need not reflect only credit risk. Huang and Huang (2004) and others show that the proportion of the credit spread attributable to default (i.e. to pure credit risk) is relatively low (20–30%) for high quality bonds

Table 4
Credit risk regression

Variable	Parameter estimate ($\hat{\beta}$)	Standard error	p-Value
Δ AA spread	5.80×10^{-5}	1.59×10^{-5}	0.0003
Δ BBB spread	-3.38×10^{-5}	9.36×10^{-6}	0.0003
\bar{R}^2 fixed effects only	56.2%		
\bar{R}^2 with fixed effects and factors	56.8%		
Average \bar{R}^2 from bank-level regressions	4.8%		
Number of observations	612		

Estimates of credit risk regressions using pooled OLS with bank fixed effects. Dependent variable is annualized net interest income less provisions. Data are from Y-9C bank holding company regulatory reports over the period 1994Q1–2002Q4 using the bank holding company sample discussed in Section 5.2. Explanatory variables are the change in the AA and BBB spreads. We use monthly data on the yield-to-maturity and Macaulay duration from the Merrill Lynch AA and BBB-rated corporate bond indices obtained from Bloomberg. We compute spreads by subtracting from each yield-to-maturity a weighted average of the 5, 7, and 10 year Constant Maturity Treasury (CMT) rates. The weights are based on the difference between the duration of the relevant index and the duration of a par 5, 7, or 10 year Treasury paying the relevant CMT rate.

but higher (60–80%) for speculative grade bonds. As a result, it is not surprising that a widening of double-A spreads actually increases credit-related returns for banks.

We now generate the market and credit risk distributions by combining the estimated factor sensitivities with simulated annual realizations of the factors based on the estimated multivariate asymmetric GARCH model. In our application, starting values for volatilities are set to their unconditional levels to reflect average market conditions. However, by setting the initial volatility levels to their current values, our model could also be used to estimate time-varying risk densities that depend on current market conditions.

For the market risk factors, which are modeled at a daily frequency, we first simulate a path of 252 daily log-returns and variances. Since the credit risk factors are estimated at a monthly frequency, we simulate a path of 12 log-returns and variances. The sum of the 252 daily or 12 monthly log-returns is equal to a single annual return, and the sum of the daily or monthly variances is equal to a single annual variance. This approach matches the market and credit risk horizons to the same annual horizon as operational risk. We repeat this procedure 200,000 times to create the simulated joint distribution of the annual factors. Each of the 200,000 simulated annual market or credit returns is simply a linear combination of the simulated annual factor realizations multiplied by the factor sensitivities.

5.5. Market and credit residual risk

From the relatively small size of the average \bar{R}^2 's in the factor sensitivity regressions, it is clear that much of the variation in accounting returns attributable to either market or credit risk related activities is not captured by our set of dynamic

Table 5

Characteristics of moments of residuals across 17 bank-specific regressions

	Std. dev. (%)	Skewness	Kurtosis
<i>Panel A: Market risk residuals</i>			
Mean	2.27	0.5	8.4
Median	1.18	0.3	7.5
Simulated	1.18	0.5	6.4
<i>Panel B: Credit risk residuals</i>			
Mean	1.25	−0.6	7.3
Median	1.04	−0.8	5.5
Simulated	1.04	−0.6	6.0

Bank-specific regressions are estimated using the same specification as the pooled OLS models. Details of the market risk regression are given in Table 3, while details of the credit risk regression are given in Table 4. In the top panel, the first row represents the cross-sectional average of the standard deviation, skewness, and kurtosis of the 17 market risk regression residuals. The bottom panel reports the same statistics for the credit risk regression residuals. Because these distributions are skewed, the median is different from the mean. The rows labeled “Simulated” denote the moments of the simulated residuals; see Section 5.4.

risk factors. This should hardly be surprising as bank-specific risk often plays an important role in total bank risk. For example, a single large obligor default can have a significant bottom line impact for an individual bank that is not common across the entire industry. Moreover, operating risk and business risk are absorbed into our estimated residual.¹¹ Operating risk includes operational risk as defined by the New Basel Accord, while business risk includes variation in earnings due to factors such as fluctuations in demand, technology shocks, and changes in the competitive landscape.

In Table 5, we present summaries of the residuals for the market and credit risk regressions. We report cross-sectional (across 17 regressions) averages and medians of moments two through four. The simulated residuals are discussed below in Section 5.7. The distribution of residuals is asymmetric and fat-tailed for both risk types, though the skew is positive for market and negative for credit risk.

It is also interesting to analyze the impact of these residuals on the total risk distribution. To conduct such an exercise, we need to obtain a representative residual distribution for market and credit risk that can then be incorporated into the overall analysis. To avoid creating excess kurtosis by combining densities with different volatilities, we first standardize each of the residuals by the respective bank-risk type residual volatility, i.e., the root mean square error (RMSE) of each bank-risk type regression. We then pool the standardized residuals across all banks for each risk

¹¹Kuritzkes (2002), for instance, contrasts “event” risk, which conforms more closely to the notion of operational risk used here, with “business” risk, which is thought to capture (p. 3) “residual nonfinancial earnings volatility not attributable to internal or external events.” He finds that event plus business risk make up about 2.5% of total risk-weighted assets (or about 30% of the BIS total capital requirement) for these institutions, of which about 58% is residual “business” risk. If we take these figures at face value, it would imply that we are missing about 15–18% of “total” risk.

type and scale them by the median RMSE of each risk type. In this way, the higher moments of the residuals are preserved but at a scale that is representative of this group of large banks. This gives us a sample of 612 residuals for each of the two risk types that can be used to define each nonparametric residual risk distribution.

5.6. Operational risk

For our empirical work, we adopt the definition of operational risk set forth by the Basel Committee. Namely, these are losses due to failure of internal processes, people, and systems, or from external events. For our analysis of operational risk, we use results from [de Fountnouvelle et al. \(2003\)](#), hereafter FJJR. They argue that the vendor-provided operational loss databases suffer from a reporting bias that is correlated with loss size: small losses are underreported while large losses are “too big to hide.” Specifically, if we denote X as a vector of operational losses, then for some reporting threshold τ , where $\tau = \$1$ million in FJJR, $x = \log(X - \tau)$ is modeled as an exponential density, $f(x) = (1/b)e^{-x/b}$. FJJR incorporate a size-bias correction and estimate the exponential parameter b to be 0.64 using the OpRisk Analytics database and 0.66 using the OpVantage database. We take the average of these values to obtain an exponential parameter of 0.65.

FJJR also report that large, internationally active banks typically experience between 50 and 80 losses, each exceeding \$1 million per year, the minimum loss value in the datasets. We take the midpoint of their range to obtain a daily probability of an operational loss event of $65/365$.¹²

We construct the annual operational loss distribution for our typical bank as follows. To create a single annual loss realization, we first draw 365 Bernoulli trials with $p = 65/365$. This reflects the possibility of an operational loss each day. On each day that an operational loss occurs, we draw the log of the dollar loss amount from an exponential distribution with parameter of 0.65. We sum the exponentials of the daily log-losses to create the annual dollar loss. The final operational risk distribution is generated using 200,000 loss years.¹³

5.7. Marginal risk distributions

While each marginal risk is simulated from a parametric model, the introduction of nonlinearities such as GARCH and associated temporal aggregation result in annual risk distributions that might be quite difficult to fit parametrically. This

¹²To be sure, we cannot directly verify that these “internationally active banks” represent the median bank in our sample. But at a minimum, this group is likely to have regulatory capital assessed for credit and market risk (under the existing capital rules) and thus should overlap substantially with our sample of 17 banks. Note also that FJJR do not find the tail thickness parameter b to vary with bank size.

¹³If $\log(X)$ is exponentially distributed, then X has a Pareto distribution (e.g., [Johnson et al. 1994](#), p. 576). Using the exponential parameter of 0.65, only the first moment of the loss distribution exists. In our simulations, we set a log-loss greater than 1,000 standard deviations equal to a loss of 1,000 standard deviations. This guarantees the existence of all moments without affecting the tail shape in the region of interest.

motivates our more robust nonparametric approach for inverse cumulative distribution function estimation. These functions are needed as inputs to the copula to generate the total risk distribution.

For each risk type, we define the empirical inverse cumulative distribution function by sorting the returns and associating with each return its rank in the dataset (divided by 200,000). We then fit a cubic spline to this function. The spline estimate is our inverse cumulative distribution for each risk type.

The characteristics of the simulated marginal risk distributions for 200,000 simulated bank-years are presented numerically in Table 6 (columns two through four) and visually in Fig. 2. In terms of assets at risk, market risk has highest volatility ($\sigma_{mk} = 0.58\%$) and thinnest tails ($\kappa_{mk} = 3.7$), while operational risk has lowest volatility ($\sigma_{op} = 0.04\%$) and fattest tails ($\kappa_{op} = 35.3$). Credit risk is in-between, with $\sigma_{cr} = 0.19\%$ and $\kappa_{cr} = 16.1$. The market risk distribution is nearly symmetric while the credit risk distribution is moderately left-skewed at -1.3 and operational risk is more significantly left-skewed at -4.5 .

The operational risk distribution is noticeably different from the other two. Volatility is relatively low, but skewness and especially kurtosis are quite high. Thus, while operational exposure typically has a small impact on risk, there are occasional extreme losses. This finding is consistent with the rare but enormous operational losses observed at financial institutions such as Allied Irish, Daiwa, and Barings (Jorion, 2001).

At this stage, it is instructive to examine the moments of the simulated market and credit residual risk distributions that are given in Table 5 in the rows labeled “Simulated.” By construction, the volatility of those residuals is the same as the empirical median. As expected, the higher moments of the simulated residuals are similar to those of the actual residuals. Market risk residuals have the positive skew and fat tails of their systematic counterpart, and credit risk residuals are similarly fat-tailed but negatively skewed. In the risk aggregation analysis (Section 6.3.3), we use these simulated residuals when including residual risk into the total risk distribution.

Table 6
Characteristics of simulated marginal risk distributions for 200,000 bank-years

	Market risk	Credit risk	Operational risk	Total risk
σ (assets at risk) (%)	0.58	0.19	0.04	0.11
σ (total book) (%)	0.02	0.05	0.03	0.08
Skewness	0.2	-1.3	-4.5	-1.1
Kurtosis	3.7	16.1	35.3	9.6
0.1 percentile (%)	-1.81	-1.20	-0.37	-0.43
0.5 percentile (%)	-1.47	-0.72	-0.27	-0.29
1st percentile (%)	-1.32	-0.57	-0.17	-0.24

All values are annualized, and the mean is zero by construction. The methods are described in Section 5.7. The total risk distribution is generated by simulating the weighted average of market (3.1%), credit (29.1%), and operational (67.8%) returns from a joint distribution defined using a normal copula with the benchmark correlations (market versus credit = 0.5, market/credit versus operational = 0.2). Assets at risk for market risk is equal to trading assets, for credit risk is equal to lending assets, and for operational risk is equal to total assets. Total book is the the sum of these three assets at risk.

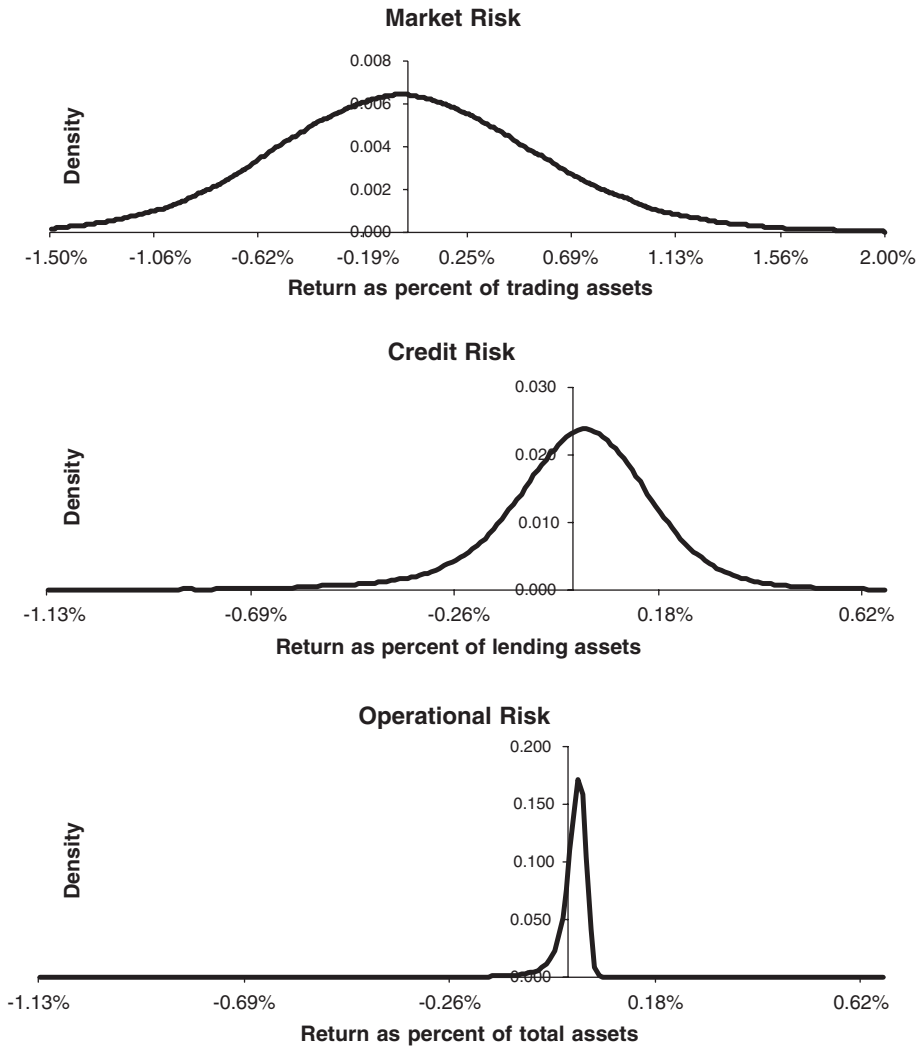


Fig. 2. Market, credit, and operational risk distributions estimated using simulated factor returns and estimated factor exposures based on methods described in Section 5.7 and summarized in Table 6. The three panels display kernel density plot (Epanechnikov kernel, Silverman's optimal bandwidth) of simulated marginal risk distributions for 200,000 bank-years.

6. Aggregating the risks

To aggregate the three risk types, we need to know their marginal distributions and the relative weight of each distribution. We then assign inter-risk correlations and specify a copula. We consider the normal copula to be a useful benchmark, since the multivariate normal distribution is commonly used in risk management, an

example being RiskMetrics (JP Morgan, 1995). A reasonable first generalization beyond the multivariate normal is to combine more realistic marginals into a joint distribution using a normal copula. The normal copula is also commonly seen in the literature. See, for instance, Li (2000) and Ward and Lee (2002).

More recently, the Student-*t* copula has become prominent (see, for instance, Frey and McNeil, 2001; Glasserman et al., 2002) because it can capture “tail dependence,” which is controlled by the degrees of freedom parameter. In contrast, a normal copula has tail independence. We report risk aggregation results for Student-*t* copulas with five and ten degrees of freedom in Section 6.3.

6.1. *Marginal risk-type weights and cross-risk-type correlations*

In Section 5.2, we determine benchmark ex ante weights for our large, internationally active bank of 3.1% for market risk, 29.1% for credit risk, and 67.8% for operational risk. Changing these weights is meant to reflect different business mixes. For example, most regional banks focus their business activities on lending and have little trading activity. As a result they are likely to have relatively more credit risk and less market risk than the base case would suggest. In addition, they could have less exposure to traditional sources of operational risk such as processing or custody-related activities. A “processing bank,” conversely, would likely have more operational risk than the average bank. Finally, one would expect a trading-intensive bank to have relatively more market risk.

KSW, in their risk aggregation exercise, examine a broad range of correlations gleaned from several academic and industry studies. They summarize these correlations in their Table 4, which we reproduce here and use in our own analysis as Table 7. The first set is taken from Dimakos and Aas (2004). The second set comes from Ward and Lee (2002), who provide separate correlations for market and ALM risk; the table entry is the larger of the two correlations. The third set is cited in Joint Forum (2001, p. 25), and is based on interview findings. This last set reflects the values used by Dutch and other financial conglomerates in their internal capital models. For our benchmark institution, we take the midpoint of these values. The resulting benchmark correlation between market and credit risk is 50%, and the benchmark correlation of each of these two risk types with operational risk is 20%.¹⁴

6.2. *Results*

The total risk distribution using the benchmark weightings and correlations with a normal copula is presented graphically in Fig. 3 and numerically in the last column of Table 6. The volatility is 0.08% of total book (defined as the sum of trading assets,

¹⁴When the marginal risks are normal, the correlations for risks combined using a normal copula are equal to the copula parameter values. Otherwise, there will be some difference between the actual correlation and the ‘ ρ values’ that are used for the copula. For our analysis across business mixes with fixed correlations, the market versus credit correlation at $\rho = 0.50$ is equal to 0.47 and the market/credit versus operational correlation at $\rho = 0.20$ is 0.16. See also Table 10.

Table 7
Inter-risk correlations (%)

	Credit	Market/asset-liability management	Operational and other
Credit	100	30 30 80	20 44 40
Market/Asset-Liability Management	30 30 80	100	20 13 40
Operational and Other	20 44 40	20 13 40	100

This is Table 4 from Kuritzkes, Schuermann, and Weiner (KSW) (2003). The entries correspond to examples of inter-risk correlations from three studies (academic and industry), as summarized in KSW, that are closely related to the risk types analyzed in this paper. The first set is taken from Dimakos and Aas (2004). The second set comes from Ward and Lee (2002), who have separate correlations for market and asset-liability management risk; the table entry is the higher of the two correlations. The third set is cited in Joint Forum (2001, p. 25), which is based on interview findings, and reflects the values used by Dutch and other financial conglomerates in their internal capital models.

lending assets, and total assets) or 0.11% of total assets. Of course, this distribution inherits features from the marginals. The negative skewness present in the credit and operational marginals is carried over into the overall skewness (−1.1). The kurtosis of total risk (9.6) is between that of market (3.7) and operational (35.3) risk.

We now use the characteristics of the benchmark total risk distribution to measure ex post contributions of each risk type. These can be compared with the ex ante business mix weights used to estimate VaR.¹⁵ We obtain ex post risk contributions at the benchmark weights of 8.5% for market, 53.1% for credit, and 38.4% for operational risk. As expected, these values differ significantly from the ex ante business mix weights, which again are 3.1% for market, 29.1% for credit, and 67.8% for operational risk. However, our ex post contributions are generally comparable to industry economic capital benchmarks; recall these are 20%, 55%, and 25% for market, credit, and operational risk, respectively.

KSW note that the bulk of the economic capital attributed to market risk using internal bank models arises from asset liability management (ALM), which is not subject to capital regulation and is not incorporated in our weights. This difference helps explain our smaller market risk attribution. Operational risk is difficult to

¹⁵We choose a relatively straightforward approach to risk attribution by applying the H-VaR formula given in Eq. (6). This approach takes into account the business mix weights, the marginal VaRs or levels of economic capital, and correlations. More involved methods could be applied, but that would go beyond the scope of our paper; see for instance, Gouriéroux et al. (2000) and Koyluoglu and Stoker (2002) for discussion on this topic.

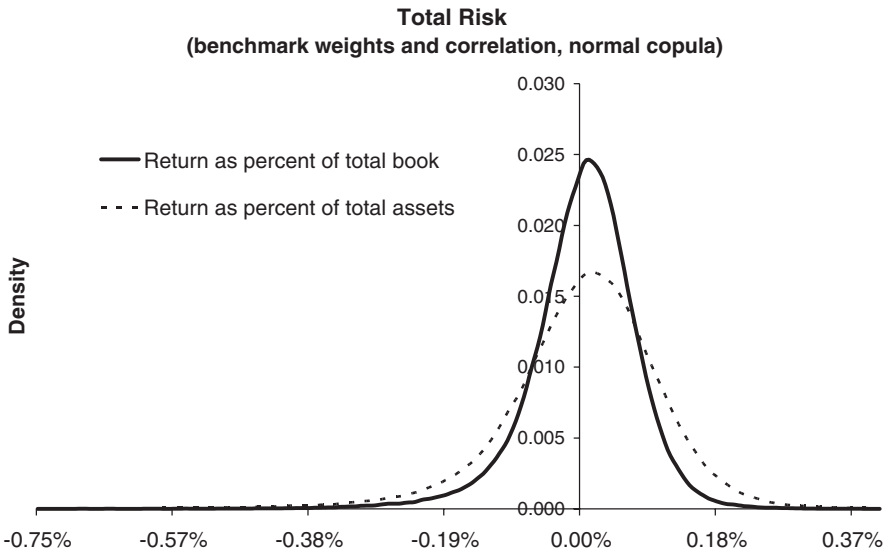


Fig. 3. Total risk distribution estimated using market, credit, and operational risks (see Table 6 and Fig. 2). These are combined using a normal copula, benchmark weights (3.1% for market risk, 29.1% for credit risk, and 67.8% for operational risk), and benchmark correlations (50% for market and credit, and 20% of those two risk types with operational risk). The figure displays a kernel density plot (Epanechnikov kernel, Silverman's optimal bandwidth) using 200,000 simulated bank-years. Total book is the the sum of trading assets, lending assets, and total assets.

measure precisely, and KSW report large differences in operational capital share allocations across industry studies. Therefore, it is not surprising that our estimate differs somewhat from the industry benchmark.

We start our discussion by focusing on the copula-based results across the two sets of experiments: varying business mix (Fig. 4 and Table 8) and inter-risk correlations (Fig. 5 and Table 9). In the figures, the line labeled “Copula” uses a normal copula with the benchmark inter-risk correlations, and the next three lines are approximations that are discussed in detail in Section 6.2.3. Following the legend, the first line is the total risk using a normal copula. The second line is the hybrid approach, which is based on an elliptical density formula for portfolio VaR as defined in Eq. (6). The third line is “Additive,” the VaR obtained by simply adding up the VaRs of the marginals. Finally, the line labeled “Normal” is the VaR under joint normality, implying, of course, that the marginal distributions are also normal.

6.2.1. Impact of business mix

In Fig. 4, we see the impact of a change in business mix on the 99.9% VaR (0.1th percentile) for the total risk distribution at the benchmark correlations. This percentile is commonly used in industry and conforms to the tolerance level of the New Basel Accord. Table 8 reports weights for the three risk types, standardized quantiles, volatilities, Copula-VaRs, and the approximation error for N-VaR and

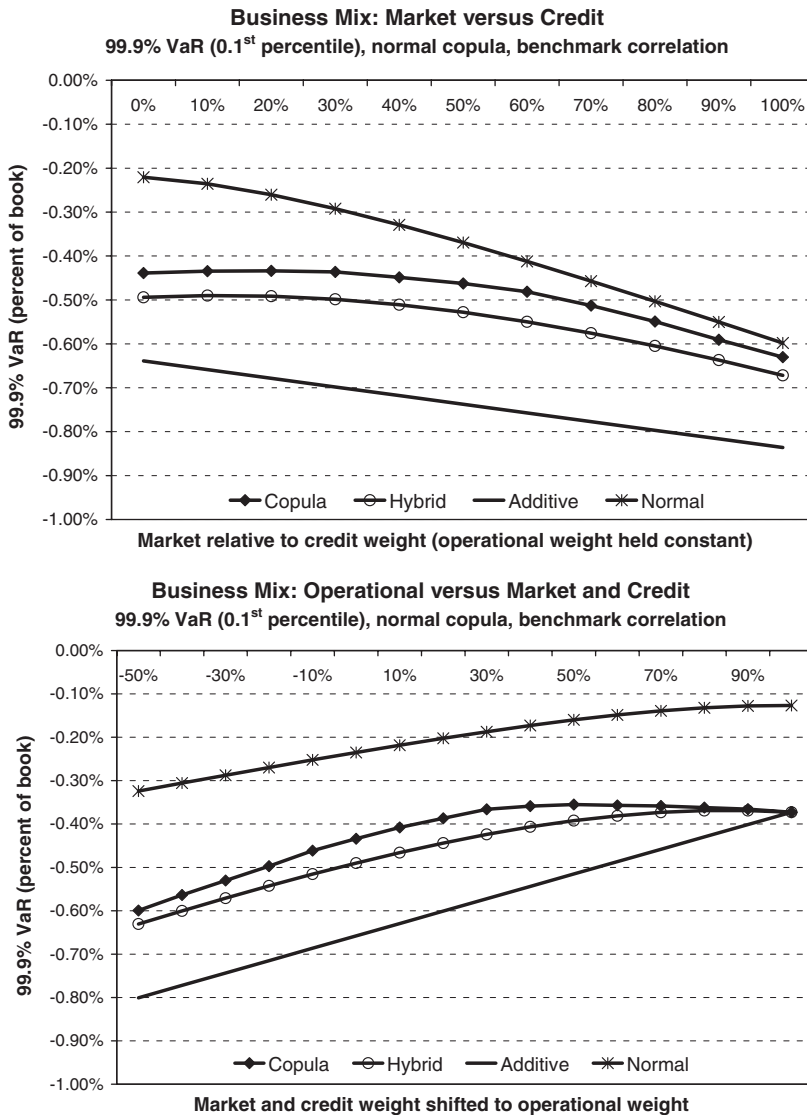


Fig. 4. Impact of business mix; 99.9% VaR (0.1% tail) of the total risk distribution. Additional detail given in Table 8. Top panel: impact of market weight relative to credit weight while holding operational weight constant. Bottom panel: impact of shift in market and credit weight to operational weight while holding relative market and credit weights constant. Both panels: normal copula with the benchmark inter-risk correlations of 50% for market and credit, and 20% of those two risk types with operational risk. In the legend, Copula is VaR computed using the copula-based total risk distribution, Hybrid (Eq. (6)) is an approximate VaR approach that combines marginal risks using a formula that would apply to an elliptical distribution, Additive adds up the marginal VaRs (Eq. (7)), and Normal (Eq. (8)) is VaR computed assuming joint normality.

Table 8
Business mix experiment

Panel A: Market versus credit risk									
Share of market vs. credit	Market weight (%)	Credit weight (%)	Operat. weight (%)	99.9% VaR (%)	Volatility (%)	Standardized quantile	Approximation Error		
							N-VaR to Copula (%)	H-VaR to Copula (%)	Add-VaR to Copula (%)
0	0.00	32.19	67.81	-0.439	0.071	-6.15	-50	13	46
10	3.22	28.97	67.81	-0.434	0.076	-5.70	-46	13	52
20	6.44	25.75	67.81	-0.434	0.084	-5.15	-40	13	56
40	12.88	19.31	67.81	-0.449	0.107	-4.21	-27	14	60
60	19.31	12.88	67.81	-0.481	0.133	-3.61	-14	14	57
80	25.75	6.44	67.81	-0.549	0.163	-3.37	-8	10	45
90	28.97	3.22	67.81	-0.591	0.178	-3.32	-7	8	38
100	32.19	0.00	67.81	-0.630	0.194	-3.26	-5	7	33

Panel B: Operational versus market and credit risk

Share shifted from market and credit to operational	Market weight (%)	Credit weight (%)	Operat. weight (%)	99.9% VaR (%)	Volatility (%)	Standardized quantile	Approximation Error		
							N-VaR to Copula (%)	H-VaR to Copula (%)	Add-VaR to Copula (%)
-50	4.65	43.64	51.71	-0.599	0.105	-5.72	-46	5	34
-30	4.03	37.82	58.15	-0.530	0.093	-5.70	-46	8	40
-20	3.72	34.91	61.37	-0.497	0.087	-5.70	-46	9	44
-10	3.41	32.00	64.59	-0.461	0.082	-5.66	-45	12	49
0	3.10	29.09	67.81	-0.434	0.076	-5.71	-46	13	52
10	2.79	26.18	71.03	-0.408	0.071	-5.77	-46	14	54
20	2.48	23.27	74.25	-0.387	0.065	-5.91	-48	15	55
30	2.17	20.36	77.47	-0.366	0.061	-6.05	-49	16	56
50	1.55	14.55	83.90	-0.355	0.052	-6.86	-55	10	45
80	0.62	5.82	93.56	-0.362	0.043	-8.47	-64	2	19
100	0.00	0.00	100.00	-0.373	0.041	-9.09	-66	0	0

Standardized quantile and volatility for 99.9% VaR (0.1% tail) of the total risk distribution as business mix changes. Business mix and risk weights are defined in Section 5.2. In panel A, each row represents market weight versus credit weight while holding the operational weight constant. The italicized row is closest to the benchmark risk weights: 3.1% for market risk, 29.1% for credit risk, and 67.8% for operational risk. Some intermediate values (rows) are omitted due to space considerations. In panel B, each row represents the *change* in operational weight, while holding the relative weights of market and credit constant. The italicized row represents the benchmark risk weights. The standardized quantiles for the market, credit and operational risk distributions are -3.12, -6.29, and -9.09, respectively. The marginal volatilities in same order are 0.58%, 0.19%, and 0.04%. Add-VaR (Eq. (7)) adds the VaRs of the marginal risk distributions, N-VaR (Eq. (8)) assumes joint normality, and H-VaR (Eq. (6)) combines marginal risks a formula that would apply to an elliptical distribution. Approximation error is (approximation VaR - Copula VaR)/Copula VaR. See also Fig. 4.

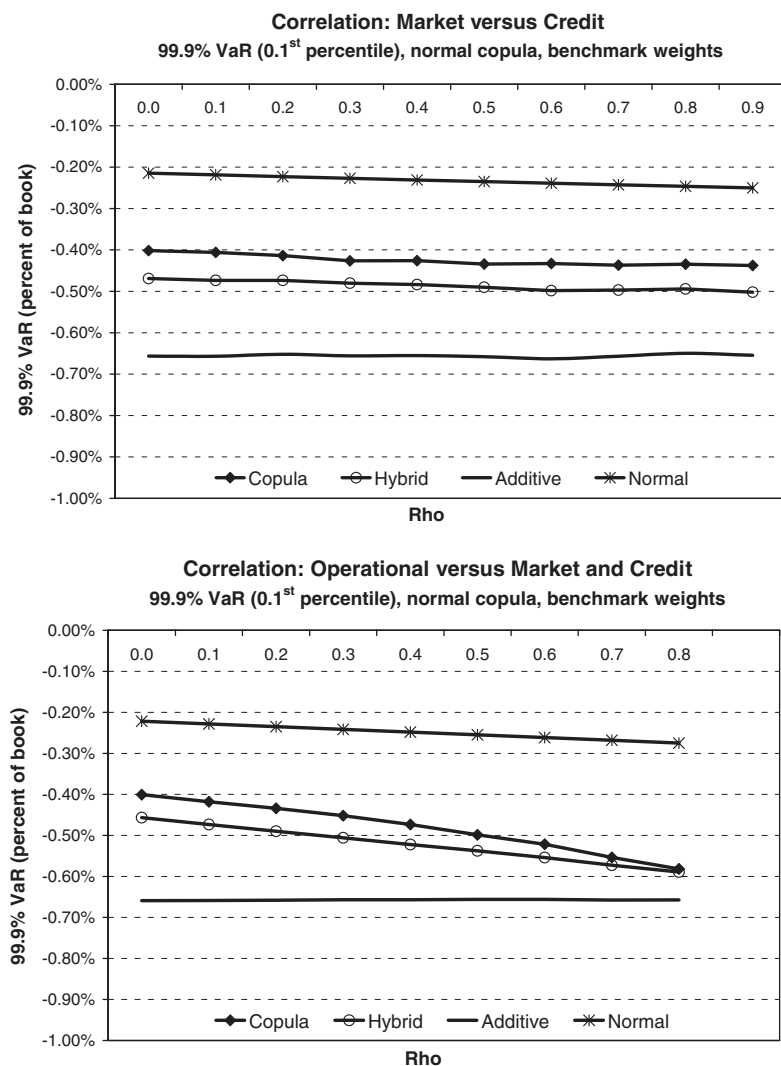


Fig. 5. Impact of inter-risk correlation (ρ); 99.9% VaR (0.1% tail) of the total risk distribution. Additional detail given in Table 9. Top panel: impact of changing correlation between market and credit risk while correlation of both risk types to operational risk remains constant at benchmark level of 20%. Bottom panel: impact of changing correlation between operational and the other two risk types while keeping the correlation between market and credit constant at benchmark level of 50%. Both panels: benchmark weights are 3.1% for market risk, 29.1% for credit risk, and 67.8% for operational risk. In the legend, Copula is VaR computed using the copula-based total risk distribution, Hybrid (Eq. (6)) is an approximate VaR approach that combines marginal risks using a formula that would apply to an elliptical distribution, Additive adds up the marginal VaRs (Eq. (7)), and Normal (Eq. (8)) is VaR computed assuming joint normality.

Table 9
Correlation experiment

ρ	99.9% VaR (%)	Volatility (%)	Standardized quantile (%)	Approximation Error			Diversification benefit (Copula) (%)
				N-VaR to Copula (%)	H-VaR to Copula (%)	Add-VaR to Copula (%)	
Panel A: Market versus credit							
0	-0.402	0.069	-5.79	-47	17	63	39
0.1	-0.406	0.071	-5.74	-46	17	62	38
0.2	-0.414	0.072	-5.74	-46	14	58	37
0.3	-0.426	0.073	-5.80	-47	13	54	35
0.4	-0.426	0.075	-5.70	-46	14	54	35
0.5	-0.434	0.076	-5.71	-46	13	52	34
0.6	-0.433	0.077	-5.60	-45	15	53	35
0.7	-0.437	0.079	-5.56	-44	14	50	34
0.8	-0.434	0.080	-5.44	-43	14	50	33
0.9	-0.438	0.081	-5.40	-43	15	50	33
Panel B: Operational versus market and credit							
0	-0.401	0.072	-5.59	-45	14	65	39
0.1	-0.418	0.074	-5.66	-45	13	58	37
0.2	-0.434	0.076	-5.71	-46	13	52	34
0.3	-0.452	0.078	-5.78	-47	12	45	31
0.4	-0.473	0.080	-5.90	-48	10	39	28
0.5	-0.499	0.082	-6.05	-49	8	32	24
0.6	-0.522	0.085	-6.17	-50	6	26	20
0.7	-0.554	0.087	-6.38	-52	3	19	16
0.8	-0.582	0.089	-6.54	-53	1	13	11

Standardized quantile and volatility for 99.9% VaR (0.1% tail) of the total risk distribution as inter-risk correlation changes. The first set presents the results of changing correlation between market and credit risk while the correlation of both risk types to operational risk remains constant at the benchmark level of 20%. The second set describes the impact of changing correlation between operational and the other two risk types while keeping the correlation between market and credit constant at the benchmark level of 50%. Note that the maximum correlation possible for the operational risk experiment (bottom panel) is 0.8; see also footnote 16 and Table 10 below. The italicized row represents the benchmark correlations. Both sets of results: benchmark weights are 3.1% for market risk, 29.1% for credit risk, and 67.8% for operational risk. Add-VaR (Eq. (7)) adds the VaRs of the marginal risk distributions, N-VaR (Eq. (8)) assumes joint normality, and H-VaR (Eq. (6)) combines marginal risks a formula that would apply to an elliptical distribution. Approximation error is (approximation VaR-Copula VaR)/Copula VaR. Diversification benefit in the last column is (Add-VaR-Copula VaR)/Add-VaR. Note that the standardized quantile for the market, credit and operational risk distributions are -3.12, -6.29, and -9.09, respectively. The marginal volatilities in the same order are 0.58%, 0.19%, and 0.04%. See also Fig. 5.

Add-VaR relative to Copula-VaR. Some intermediate values (rows) are omitted due to space considerations. The standardized quantile (VaR/volatility) provides a measure of left-tail thickness. A normal distribution has a standardized 0.1% quantile of -3.1 , so larger negative values indicate a relatively fat left tail.

The top panel in Fig. 4 displays the effects of varying market versus credit weight while holding the operational weight constant at its benchmark level of 67.8%. Thus, the leftmost set of points corresponds to 0% market and 32.2% credit risk, the next set of points corresponds to 3.2% market and 29.0% credit risk, and at the other extreme we have 32.2% market and 0% credit risk. Naturally, the extreme points are rather unrealistic, but we can view the intermediate weights as reasonably reflecting different business mixes from, for example, little to more intensive trading activity.

With 0% market and 32.2% credit weights, the volatility of the total risk distribution is 0.071% and the 0.1% standardized quantile is -6.15 standard deviations (Table 8, panel A, first row). At first, VaR declines as market exposure increases; that is, the initial decrease in left-tail thickness (market has thinner tails than credit) outpaces the volatility increase (market has higher volatility than credit). At a market risk share larger than 30%, which corresponds to a market weight of around 9%, the volatility increase starts to dominate, giving the VaR curve a parabolic shape. VaR ranges from a low of -0.434% to a high of -0.630% , with the lowest risk achieved near the benchmark exposure weights, which corresponds to the italicized row in Table 8, panel A.

The bottom panel of Fig. 4 and panel B of Table 8 show the impact of a *change* in operational risk share, holding the relative proportion of the market and credit exposures constant. In the bottom panel, 0% on the horizontal axis represents the benchmark weighting, i.e., 3.1% market, 29.1% credit, and 67.8% operational risk. A shift of +10% from market and credit towards operational risk would result in respective weights of 2.8%, 26.2%, and 71.0%, and so on (see also panel B in Table 8). Since it is conceptually not reasonable to assign a weight of zero to operational risk, we adopt this approach based on deviations from the benchmark weighting.

As weights are shifted from market and credit risk, there is an increase in tail thickness (Table 8, panel B, where the italicized row corresponds to the benchmark). The left tail gets thicker as operational exposure rises. The standardized quantile at baseline weights is -5.71 standard deviations, and it increases to -9.09 standard deviations for a bank with all operational risk. At the same time, as the operational weight increases, the volatility of total risk declines (from 0.105% to 0.041%). The net effect is that the VaR curve first declines, as volatility decreases more quickly than tail-thickness increases. At operational weights greater than 50% above the benchmark, the curve flattens, reflecting the offsetting effects of decreased volatility and fatter tails.

If we decrease the weight on operational risk and shift it proportionately to market and credit risk, i.e., we move to the left in Fig. 4, overall volatility and risk (as measured by 99.9% Copula-VaR) increase. At first, the standardized quantile declines (in absolute value) from -5.71 to -5.66 . Past a 20% shift in the weights from operational to market and credit risk, it rises again to about the benchmark

level. The much larger volatility of both market and credit risk dominate the reduction in kurtosis from the operational risk distribution. To be sure, credit risk is itself also quite leptokurtic ($\kappa_{cr} = 16.1$).

6.2.2. Impact of inter-risk correlation

In Fig. 5, we explore the impact of inter-risk correlation on 99.9% VaR (the 0.1th percentile) of the total risk distribution at the benchmark risk weights. Its companion table (Table 9) shows standardized quantiles, volatilities, Copula-VaRs, and the approximation error for N-VaR and Add-VaR relative to Copula-VaR. We italicize the row corresponding to the benchmark correlations. The top panels of Fig. 5 and Table 9 display the impact of changing correlation between market and credit risk while the correlation of both risk types with operational risk remains constant at the benchmark level of 20%. The bottom panels examine the impact of changing correlation between operational and the other two risk types while keeping the correlation between market and credit constant at the benchmark level of 50%.¹⁶

As expected, higher levels of market and credit risk correlation lead to higher levels of risk as measured by VaR (Fig. 4, top panel and Table 9, panel A).¹⁷ VaR increases from -0.402% at a correlation of zero to -0.438% for a correlation of 0.9. We see that higher market and credit correlation is associated with higher volatility and a slightly thinner left tail. Overall, however, the impact of changing the inter-risk correlation between market and credit risk has a rather small impact on total risk.

Looking now at the bottom panel in Fig. 5 and panel B in Table 9, VaR increases as we raise the correlation between operational risk and market/credit risk. From an initial level of -0.401% at zero correlation, VaR increases to -0.582% at a correlation of 0.8. In this case, higher correlation results in higher volatility and a fatter left tail. Since both of these effects are in the same direction, total risk is more sensitive to the level of operational risk correlation with other risk types than the level of market versus credit correlation.

Deviation from normality in the marginal distributions drives a wedge between ρ and the correlation coefficient. This is illustrated in Table 10, where we display the relation between the two from simulated returns using a normal copula. The first column corresponds to the top panel of Fig. 5 while the second column corresponds to the bottom panel.

While the market and credit correlation (column 1) is always quite close to the specified ρ (within 0.03), the operational versus market/credit correlation is somewhat lower (column 2). As ρ varies from 0.10 to 0.80, the market and credit correlation moves from 0.09 to 0.77, but operational correlation moves from 0.08 to 0.67. Even though operational risk correlation has a smaller range for these experiments, VaR is more sensitive to changes in operational ρ than market versus credit ρ . In our calculation of VaR approximations (including N-VaR), we use the

¹⁶Of course, one can not construct a correlation matrix from arbitrarily assigned correlations. The Cholesky factorization used for simulation requires the correlation matrix to be invertible. Thus, for some experiments we are not able to set $\rho_{i,j}$ for any risk type i or j to be arbitrarily high.

¹⁷Embrechts et al. (2002) give examples of increased ρ leading to lower VaR.

Table 10
Relation between ρ and correlation

ρ	Correlation (market, credit)	Correlation (operational, {market, credit})
0.1	0.09	0.08
0.2	0.19	0.16
0.3	0.28	0.24
0.4	0.38	0.32
0.5	0.47	0.40
0.6	0.57	0.49
0.7	0.67	0.58
0.8	0.77	0.67

Relation between ρ and correlation from a multivariate distribution created using simulated returns (see Table 6) and a normal copula with benchmark weights (3.1% for market risk, 29.1% for credit risk, and 67.8% for operational risk). The second column corresponds to the top panel in Fig. 5, where the correlation between market and credit is allowed to change while each of their correlations with operational risk remains fixed at the benchmark level ($\rho = 20\%$). The third column corresponds to the bottom panel of Fig. 5, where the correlation between market and credit stays fixed at the benchmark level ($\rho = 50\%$) as it changes with respect to operational risk and the other two risk types.

empirical correlation matrix, rather than the ρ matrix, so that comparison across VaR estimates are based on equal correlations.

6.2.3. Approximations to Copula-VaR

In comparing the three VaR approximations to the copula method (Figs. 4–7, Tables 8–9), we see several patterns. First, Add-VaR always provides the largest VaR estimate, and N-VaR always provides the smallest estimate. Both are significantly biased relative to Copula-VaR. Add-VaR overestimates risk, since it fixes the correlation matrix at unity, when in fact the empirical correlations are much lower. N-VaR underestimates risk since it uses the lowest standardized quantiles for the marginals, i.e. $\Phi^{-1}(0.001) = -3.09$, versus actual quantiles of -3.12 (market), -6.29 (credit), and -9.09 (operational). The hybrid approach (H-VaR) tracks Copula-VaR well, but it is also upwardly biased and thus conservative.

In Tables 8 and 9, we contrast the approximate VaRs with Copula-VaR by computing the approximation error, which is equal to (approximation VaR – Copula-VaR)/Copula-VaR. In the business mix experiment (Fig. 4 and Table 8), Add-VaR is monotonically decreasing as we shift to a lower volatility risk type. If we assume that the joint distribution is normal (N-VaR), then total risk increases modestly (Fig. 4, top panel and Table 8, panel A). Indeed, N-VaR initially underestimates VaR by about 50%, but comes within 5% as the share of market versus credit risk goes to 100%. Note that, of the three risk types, the market risk distribution is closest to normal. H-VaR is within 14% (no market risk exposure) to 7% (no credit exposure) and has the same parabolic shape as the copula

measurement. Add-VaR overestimates Copula-VaR by between 33% (no credit exposure) and 60% (market and credit risk weights of 12.88% and 19.31%, respectively).

In the bottom panel of Fig. 4 and panel B of Table 8, we see that as the business mix shifts towards operational risk, copula, H-VaR, and Add-VaR converge. Copula-VaR and H-VaR pick up the tradeoff between lower volatility and heavier tails, so they both flatten. N-VaR shrinks steadily, as it is driven entirely by volatility (which is lowest for operational risk), and ignores the very heavy tails inherited from the operational risk distribution.

Moving on to the correlation experiments (Fig. 5 and Table 9), we find that H-VaR tracks Copula-VaR fairly well, although H-VaR is always more conservative. The maximum approximation error of H-VaR from Copula-VaR is 17% across all correlation experiments with an average approximation error of 14% for market/credit and 9% for operational correlations. The average approximation error for N-VaR is -45% when varying market versus credit correlations and -48% when varying the operational correlation. This reflects the overly thin left tail of the normal distribution compared to the actual risk distributions. N-VaR also changes approximately linearly with ρ , while Copula-VaR and H-VaR reflect nonlinear interactions of the tails with the correlation.

For the correlation experiments, we also compute a “diversification benefit,” which is the percentage decrease in VaR using the copula approach versus Add-VaR: $(\text{Add-VaR} - \text{Copula-VaR}) / \text{Add-VaR}$. This statistic is of interest because it provides a benchmark for the degree of conservatism that comes with the additive VaR rule. This conservatism might be thought of as providing a buffer against parameter and model uncertainty. Given the benchmark business mix weights, we find diversification benefits of 33–39% when varying market versus credit correlations and of 11–39% when varying the operational correlation. These are generally higher than the 15% diversification benefit reported by KSW, although KSW use the 99% VaR level and assume joint normality. Our results are closer to the 20+ % reported by Dimakos and Aas (2004), who also use a normal copula and look at the far tail (99.97% in their case).

Taken together these results imply that the interaction between measures of correlation and the higher moments of the marginals is quite subtle and complicated. Add-VaR systematically overestimates total risk while N-VaR underestimates total risk. H-VaR provides a fairly close approximation.

6.3. Robustness tests

6.3.1. Risk measure

Since VaR is not a coherent risk measure based on the criteria of Artzner et al. (1999), we repeat the set of experiments using the expected shortfall (ES) measure as defined in Eq. (2). The general conclusions are no different from our previous findings using VaR. By way of illustration, we present in Fig. 6 two experiments focusing on risk sensitivity to operational exposure and operational correlation.

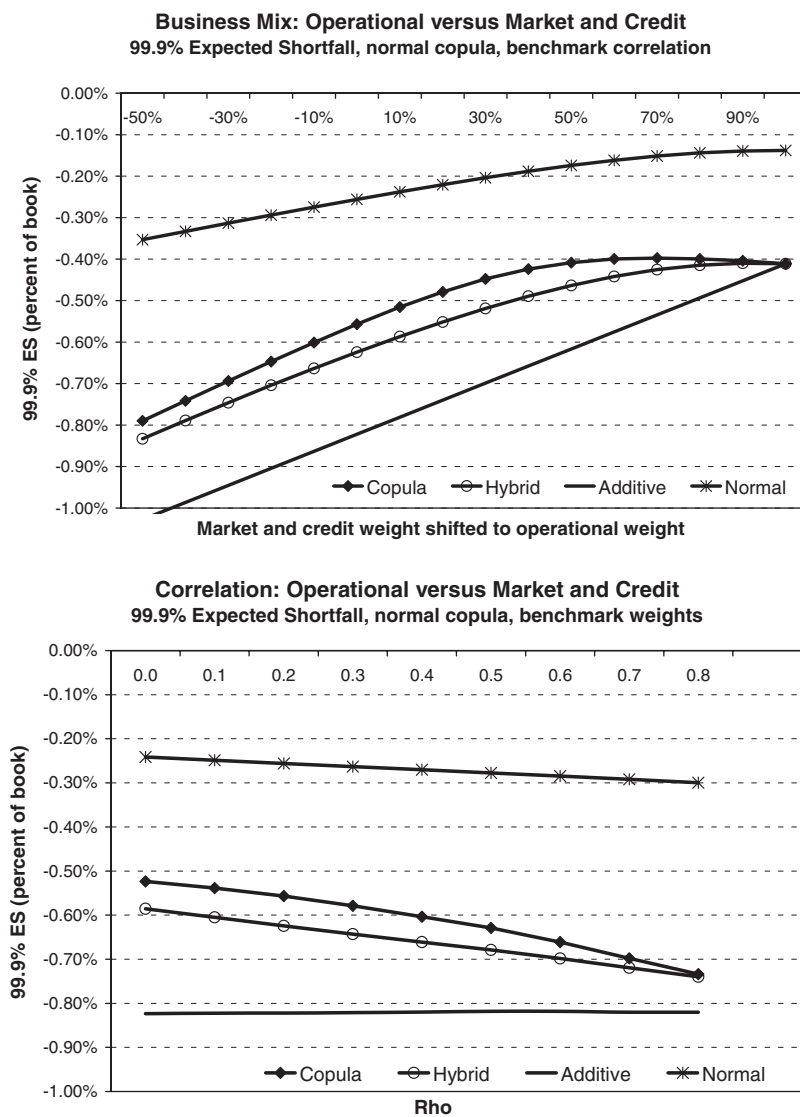


Fig. 6. Impact of business mix and inter-risk correlation on the 99.9% expected shortfall (ES) of the total risk distribution. Top panel: impact of shift in market and credit weight to operational weight while holding relative market and credit weights constant; analogous to bottom panel of Fig. 4. Bottom panel: impact of changing correlation between operational and the other two risk types while keeping the correlation between market and credit constant at the benchmark level of 50%; analogous to bottom panel of Fig. 5. In the legend, Copula is VaR computed using the copula-based total risk distribution, Hybrid (Eq. (6)) is an approximate VaR approach that combines marginal risks using a formula that would apply to an elliptical distribution, Additive adds up the marginal VaRs (Eq. (7)), and Normal (Eq. (8)) is VaR computed assuming joint normality.

The top panel of Fig. 6 shows the impact on 99.9% ES of a *change* in operational risk weight, holding the relative proportion of the market and credit weight constant. This is analogous to the VaR results displayed in the bottom panel in Fig. 4. Similarly, the correlation experiment in the bottom panel of Fig. 6 examines the impact on 99.9% ES of changes in correlation between operational risk and the other two risk types while keeping the correlation between market and credit risk constant at the benchmark level of 50%. This figure is analogous to the bottom panel of Fig. 5.

While expected shortfall is always greater than VaR (as guaranteed by definition), their sensitivities to changes in business mix and correlation are very similar. For example, in the bottom panel of Fig. 6, copula ES follows the same pattern as copula VaR (bottom panel of Fig. 5), but is consistently about 5–10% larger. Remarkably, even for expected shortfall, the hybrid ES comes quite close to the copula ES (on average within 13%, nearly the same as for VaR), albeit always with a positive bias.

6.3.2. Copula choice

To measure VaR sensitivity to the choice of copula, we repeat the experiments forming joint distributions using Student- t copulas to allow for tail dependence, which is determined by the degrees of freedom parameter ν . Choices for strong tail dependence in the literature range from a ν of between three and seven (Glasserman et al. 2002) or between three and eight (Demarta and McNeil, 2005), so we take a midpoint of $\nu = 5$. For a case between strong tail dependence ($\nu = 5$) and tail independence (normal copula, $\nu = \infty$), we use $\nu = 10$. See also Embrechts et al. (2002).

The results are presented in Fig. 7, where the top panel shows the business mix experiment with operational risk, and the bottom panel shows the inter-risk correlation experiment, which is analogous to the previous figure on expected shortfall. Two features stand out in both experiments. First, there is relatively little difference in risk across copula choice, although as expected, measured risk is higher when allowing for tail dependence. In the top panel wherein we vary business mix, the average proportional VaR difference using the $t(10)$ ($t(5)$) instead of the Gaussian copula is 4% (9%). The maximum deviation is 9% (17%) when operational exposure is 30% higher than the benchmark. Looking at the correlation experiment in the bottom panel, the average proportional differences are very similar to the previous experiment at 4% (10%). The maximum deviation of 5% (14%) occurs at $\rho = 0.1$, which is slightly below the benchmark correlation of 0.2.

Second, in both experiments, risk implied by the hybrid method is very close to the $t(5)$ copula. The average deviation in both cases is just 1%, with a maximum of 2% for the business mix and 3% for the correlation experiment. The positive bias of the hybrid method relative to the Gaussian copula observed earlier is on the order of incorporating some tail dependence, which from a practical perspective is perhaps not an unreasonable degree of conservatism. Although we report only results for these two experiments, they are very similar across all experiments, whether risk is measured by VaR or ES.

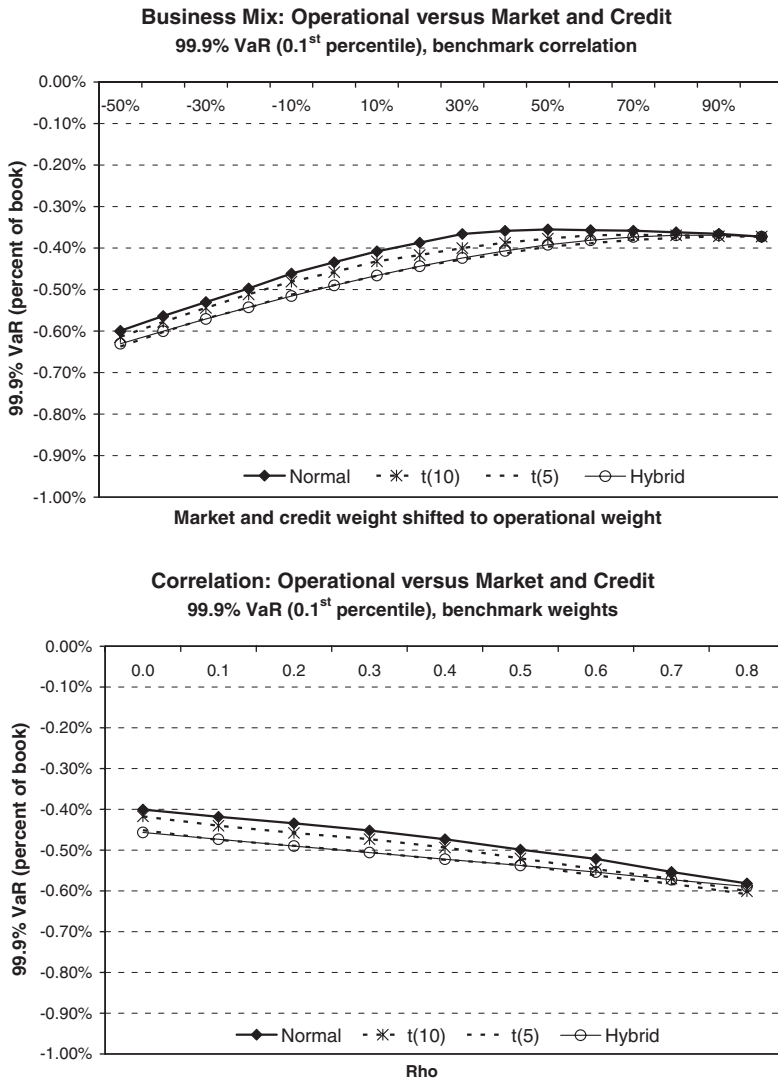


Fig. 7. Sensitivity to choice of copula. The 99.9% VaR (0.1% tail) is computed for joint distributions created using three different copulas: Normal is computed using the normal copula, and $t(10)$ and $t(5)$ are computed using the Student- $t(v)$ copula for $v = 5, 10$. Hybrid (Eq. (6)) is an approximate VaR approach that combines marginal risks using a formula that would apply to an elliptical distribution. The top panel shows impact of changing business mix, and the bottom panel shows impact of changing inter-risk correlation on the 99.9% VaR (0.1% tail) of the total risk distribution (analogous to Fig. 6 above).

6.3.3. Residual risk

As discussed in Section 5.4, the regressions for market and credit risk are unlikely to capture all the relevant risk for each risk type. Some of the “residual” in both cases will be operational risk as defined here, as well as business and other types of

risk. Nonetheless, it is instructive to examine the impact of this “residual” risk on the total risk distribution by adding simulated residuals for market and credit risk, as described in Section 5.5, to their respective returns from the factor model. Since operational risk is not modeled using the factor approach, we have no such residual here.

In keeping with the set of experiments presented in Section 6.3, the top panel in Fig. 8 shows the business mix experiment with operational risk. This can be compared to the bottom panel in Fig. 4. The bottom panel of Fig. 8 shows the inter-risk correlation experiment, which can be compared to the bottom panel of Fig. 5.

These new results are broadly in line with the experiments without residual risk. Consider first Copula-VaR; we notice immediately by looking at the scale of the vertical axis that the total amount of risk has nearly doubled. This reflects the large share of unexplained variance in our factor regressions. However, the basic features of the residual risk distributions, as characterized by their moments, are quite similar to the systematic risk distributions (see previous discussion in Section 5.7 as well as Table 5). Thus, we find that while the scaling has changed, the basic shapes of the VaR curves are similar with or without residual risk.

The results of the business mix experiment shown in the top panel of Fig. 8 are comparable to the no residual risk experiment in the bottom panel of Fig. 4, albeit with a steeper slope. At 100% operational risk weight, total risk is unchanged from the earlier experiment. When residual volatility is added to the high volatility risk types (market and credit), total risk is higher when these types have positive weight. Note that the flattening of the total risk curve happens later when residual risk is included. In this case, a greater operational weight is required for the fat left tail of operational risk to offset the new higher volatilities of market and credit risk.

These basic observations carry over to the correlation experiment shown in the bottom panel of Fig. 8. Copula-VaR is substantially higher now that residual risk is included for market and credit risk. However, Copula-VaR is much less sensitive to changes in operational correlation with the other risk types, so the VaR curves are flatter. As this correlation increases from 0.0 to 0.8, the proportional VaR increase with no residual risk is 45% (bottom panel of Fig. 5), compared to 7% with residual risk. Interestingly, the hybrid approximation seems to pick up more of the fat tails in operational risk as ρ increases. Previously, H-VaR converged to Copula-VaR, whereas now it remains below Copula-VaR (i.e., risk is higher) across the spectrum of ρ values.

6.4. Sensitivity analysis

Finally, to assess the relative importance of variation in the determinants of total risk across all of the business mix and correlation experiments, we calculate the range of VaRs across each experiment type. We then take the absolute difference between the largest and smallest VaR (within the experiment) and divide by the average VaR. The result is the proportional range of VaRs due to the variation of the chosen factor (Table 11). A wide range of VaRs indicates high sensitivity to the factor being varied.

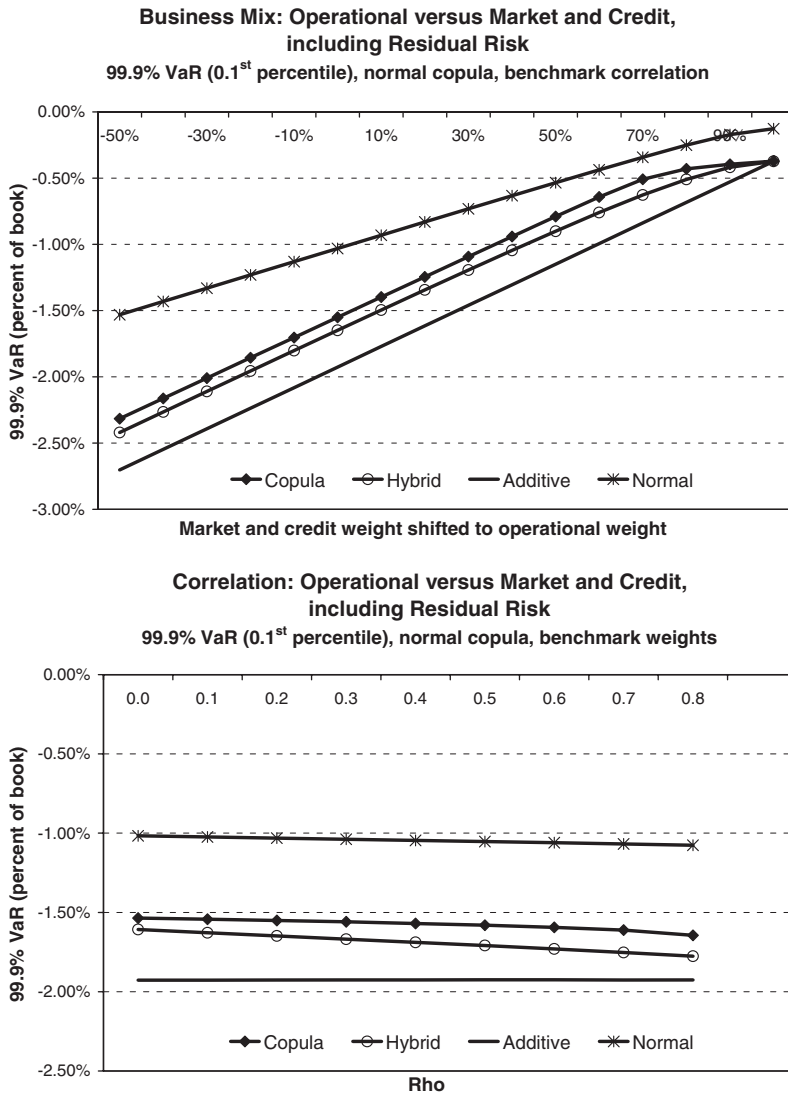


Fig. 8. Impact of residual risk on the 99.9% VaR (0.1% tail) of the total risk distribution. Top panel: impact of shift in market and credit weight to operational weight while holding relative market and credit weights constant; analogous to bottom panel of Fig. 4. Bottom panel: impact of changing correlation between operational and the other two risk types while keeping the correlation between market and credit constant at the benchmark level of 50%; analogous to bottom panel of Fig. 5. In the legend, Copula is VaR computed using the copula-based total risk distribution, Hybrid (Eq. (6)) is an approximate VaR approach that combines marginal risks using a formula that would apply to an elliptical distribution, Additive adds up the marginal VaRs (Eq. (7)), and Normal (Eq. (8)) is VaR computed assuming joint normality.

Table 11
Risk sensitivities

Factor	Average risk sensitivity (%)
Operational risk exposure	58
Approximation choice	
Add-VaR	45
N-VaR	–42
H-VaR	11
Operational risk correlation	45
Market versus credit risk exposure	40
Copula choice	10
Market versus credit risk correlation	8

Range of 99.9% VaRs (0.1% tail) across different factors and experiments in descending order. Average risk sensitivity is $|\text{Maximum VaR} - \text{Minimum VaR}| / \text{Average VaR}$, using the maximum or minimum VaR entries across the respective business mix (Table 8) and correlation (Table 9) experiments. Risk sensitivities for exposure experiments are from Table 8 and for correlation experiments from Table 9. We calculate approximation error as $(\text{approximation VaR} - \text{Copula VaR}) / \text{Copula VaR}$. We report averages of these values under “Approximation choice” in the table. Add-VaR (Eq. (7)) adds the VaRs of the marginal risk distributions, N-VaR (Eq. (8)) assumes joint normality, and H-VaR (Eq. (6)) combines marginal risks a formula that would apply to an elliptical distribution. Copula choice is the average proportional difference for VaR using the Student- $t(5)$ copula versus the normal copula versus across the business mix and correlation experiments reported in Fig. 7.

As an example, for changes in operational risk correlation, we have the largest VaR of -0.582% at a correlation of 0.8 and the smallest VaR of -0.401% at a correlation of zero. Using the average VaR of -0.482% , the relative sensitivity is 45%. To measure sensitivity to approximation choice, we average the approximation errors across business mix and correlation experiments. For risk sensitivity to copula choice, we take the average proportional VaR difference using a Student- $t(5)$ copula versus a normal copula across the business mix and correlation experiments reported in Fig. 7. For these last two measures, we first average within each experiment and then across experiments.

As shown in Table 11, the greatest risk sensitivities are to operational risk exposure, approximation choice (for Add-VaR and N-VaR), and operational risk correlation. These are followed by market versus credit risk exposure, copula choice, and market versus credit correlation. From this ordering, we see that assumptions about operational exposures and correlations are much more important for accurate risk estimates than assumptions about relative market and credit exposures or correlations. Risk measurements are also quite sensitive to approximation choice. Adding up the marginal risks or using a joint normal risk distribution results in approximation errors of 45% or -42% , respectively. Finally, the choice of copula seems to have a relatively modest impact with the next-to-lowest risk sensitivity of 10%.

7. Final comments

How would one aggregate market, credit, and operational risk distributions to arrive at a total risk distribution for a financial institution? One solution is to simply sum the various risks. Among other things, this method assumes no diversification benefits that might accrue across risk types due to imperfect correlation. Our analysis shows that the additive approach overestimates risk by more than 40%. A typical alternative, assuming joint normality of the risks, underestimates risk by a similar amount.

In this paper, we implement a method to combine these risks using copulas. Our approach forms a joint distribution from specified marginals in an internally consistent and realistic manner while preserving important properties about the individual risks. We find that interaction at the portfolio level between measures of correlation and the higher moments of the marginals is quite subtle and complicated.

Because the operational risk distribution has much heavier tails than a normal distribution, we find that risk is especially sensitive to the chosen level of operational exposure and correlation with market and credit risk. Our results suggest that approximations that might work well for combining market and credit risk tend to fail in combining the three risks because of the operational risk's unique characteristics. This could have important implications for risk managers and regulators since not only is operational risk difficult to measure, but it also requires special care in aggregation.

We also identify a hybrid approximation that tracks the copula method quite well, especially if the risks are thought to exhibit tail dependence. The hybrid approach has the advantage of being relatively easy to compute as only information about the marginals and the correlation matrix are needed.

What are some implications of our findings for the capital allocation problem faced by the financial institution? We take business mix weights as given, although, of course, these are the result of an internal process that balances risk and expected return. We abstract from this decision process by setting expected returns to zero. To be sure, the choice of business mix depends not only on risk but also on expected profits, lest one conclude that all banks would optimally choose to lower their risk by reducing lending and trading activities. When the risk measure used is sensitive to tail events, business lines with low volatility and high skewness could be less attractive, require more capital, and require higher expected returns.

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