Underestimation of Sector Concentration Risk by Mis-assignment of Borrowers[1]

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Abstract

In this paper, we investigate underestimation of sector concentration risk caused by assigning borrowers to wrong sectors.

We consider a multi-factor default-mode Merton model with infinite granularity, and evaluate the influence of a portfolio manager's mis-assignment of borrowers on estimation of model parameters and risk computation. The evaluations are made under following two conditions; 1) The true sector definitions are made in advance, and a portfolio manager assigns each borrower to one of them with a possibility of mis-assignment to a wrong sector, 2) The portfolio manager defines sectors with a possibility that the definitions differ from the true sector definitions, and the borrowers are assigned to the sectors according to the manager's definition. Under Condition 1, the true values of model parameters in terms of systematic factors are known to the manager, and parameters concerning idiosyncratic part (such as factor loadings) are estimated by the manager according to historical data. Under Condition 2, the systematic factors themselves are defined by the manager and their parameters are also estimated by the manager. To evaluate the influence of the mis-assignment purely, we assume that the portfolio is infinitely fine-grained, and that the manager can utilize enough historical data to estimate the parameters without statistical fluctuations. We derive the values of parameters which the portfolio manager will estimate and input to his risk simulator for each case, and compute 99.9%-VAR using the values.

By several experiments, we show that mis-assignment of borrowers generally leads to underestimation of the portfolio risk, and the amount of underestimation is generally larger under Condition 1 than that under Condition 2. These results suggests that to reduce the amount of underestimation, a portfolio manager should define suitable sectors for the portfolio but not use previously prepared general sector definition intact.

[1]The views or opinions in this paper are those of the authors and do not necessarily reflect those of the Financial Services Agency.

1 Introduction

Multi-factor Merton-type portfolio models of credit risk have become very popular. To compute risk of the portfolio by these models, Monte Carlo simulations are generally executed, while the IRB approach in Basel 2 adopts an approximation trick to give analytical forms of VaR of the portfolio by assuming infinite granularity and single systematic factor in the portfolio[1][2][6]. In the case where the assumptions do not hold well, accuracy of the approximation decreases. In this paper, we call the difference between the true risk and the above approximated risk as *concentration risk*.

Several techniques for analytical measurement of concentration risk have been developed. For example, Gordy proposed granularity adjustment techniques to estimate the concentration risk caused by breaking of the first assumption (infinite granularity)[2][3], and Pykhtin has developed a multi-factor adjustment technique to estimate the concentration risk cased by breaking the second assumption of single systematic factor[5]. Here, we call the second type concentration risk as *sector concentration risk*.

In these techniques, adjustment amounts are given by functions of *true* granularity index of portfolio or *true* parameters of the multi-factor model. Also, in cases of computing concentration risk by Monte Carlo simulations, these true values are necessary. Practically, the true granularity index can be calculated from the portfolio data, but the true parameters of the multi-factor model such as correlations among systematic factors or factor loadings cannot be calculated from the portfolio data. These parameters must be estimated from historical data of asset returns after sectors of borrowers are defined correctly and the borrowers are assigned to the right sectors consistently with the systematic factors in the *true* model.

If one wants to make the optimal sector definition and borrower assignment for the given portfolio, using one of statistical model selection theories (for example, [4]) based on historical asset return data will be a natural solution. However, the definition and assignment are generally made manually based on geographic regions or business sectors in practice, because of computation time, or readability of definition, or efficiency of portfolio management etc. Then, some of the borrowers might be assigned to wrong sectors, and some of the parameters needed to compute the *true* risk of the portfolio might be estimated incorrectly. Under this kind of risk management conditions, the computed portfolio risk (and sector concentration risk) will differ from the true value. Therefore, it is very important to evaluate the impact of incorrect assignment of borrowers on the portfolio risk measurement.

In this paper, we investigate underestimation of sector concentration risk caused by assigning borrowers to wrong sectors.

We consider a multi-factor default-mode Merton model with infinite granularity, and evaluate the influence of a portfolio manager's mis-assignment of borrowers on parameter estimation and risk computation. The evaluations are made under following two conditions; 1) The true sector definitions are made in advance, and a portfolio manager assigns each borrower to one of them with a possibility of mis-assignment to a wrong sector, 2) The portfolio manager defines sectors with a possibility that the definitions differ from the true sector definitions, and the borrowers are assigned to the sectors according to the definition made by the manager. Under Condition 1, the true values of model parameters in terms of systematic factors are known to the manager, and parameters concerning idiosyncratic part (such as factor loadings) are estimated by the manager according to historical asset return data. Under Condition 2, the systematic factors themselves are defined by the manager, and their parameters are also estimated by the manager. To evaluate the influence of the mis-assignment purely, we assume that the portfolio is infinitely fine-grained, and that the manager can utilize enough historical data for convergence of parameter estimations[2]. We derive the values of model parameters which the portfolio manager will estimate and input to his risk simulator for each case, and compute 99.9%-VAR using the values.

By several experiments, we show that mis-assignment of borrowers generally leads to underestimation of the portfolio risk, and the amount of underestimation is generally larger under Condition 1 than that under Condition 2. These results suggests that to reduce the amount of underestimation, a portfolio manager should define suitable sectors for the portfolio but not use previously prepared general sector definition intact.

2 Model

We consider a multi-factor default-mode Merton model in this paper. Let M be the number of borrowers.

Borrower i will default within a chosen time horizon with probability p_i. Default happens

[2]Estimations do not necessarily converge to the parameter values of true model in these conditions where the manager mis-assigns borrowers.

when a continuous variable Xi describing the financial well-being of borrower i at the horizon falls below a threshold. We assume that variables {Xi} (which may be interpreted as the standardized asset returns) have standard normal distribution. The default threshold for borrower i is given by $N^{-1}(p_i)$, where $N^{-1}(\cdot)$ is the inverse of the cumulative normal distribution function.

We assume that $\mathbf{X} = (X_1, \ldots, X_M)$ is distributed according to a multi-dimensional normal distribution, and $\mathbf{X}$ depends on K normally distributed systematic risk factors $Y_1, \ldots, Y_K$:

$$X_i = r_i Y_{Sec(i)} + \sqrt{1 - r_i^2}\xi_i,$$

where Y_S is a *composite* systematic factor (see [5] for example) of S-th sector, $Sec(i)$ is the sector that borrower i belongs to ($Sec(\cdot) : \{1, \cdots, M\} \to \{1, \cdots, K\}$). For example, Sector 1 corresponds to computer industry in Germany, Sector 2 corresponds to computer industry in Japan, Sector 3 corresponds to electricity industry in Germany, and Sector 4 corresponds to electricity industry in Japan, and so on. $Sec(3) = 2$ means that borrower 3 belongs to computer industry in Japan. Factor loading r_i measures borrower i's sensitivity to the systematic risk. ξ_is are the standardized normally distributed independent idiosyncratic shocks. Without loss of generality, we can assume $\mathrm{E}[Y_S] = 0$ and $\mathrm{V}[Y_S] = 1$ for all S (standardized systematic factor). Let $\sigma_{SS'}$ denote the correlation between Y_S and $Y_{S'}$, and let σ denote the covariance matrix of $\mathbf{Y} = (Y_1, \cdots, Y_K)$.

Let us consider a portfolio consisting of subset of the above borrowers. Let A_i denote the principal of the i-th borrower, and w_i be the relative value of A_i, $w_i = A_i / \sum A_j$. If $A_i > 0$ then borrower i is in the portfolio, and $A_i = 0$ means borrower i is not in the portfolio.

Assuming LGD = 100%, portfolio loss rate is written as the weighted average of individual losses:

$$L = \sum_{i=1}^{M} w_i \mathbf{1}\{X_i \leq N^{-1}(p_i)\},$$

where $\mathbf{1}\{\cdot\}$ is the indicator function.

In the infinite granularity setting[2], the conditional limit loss rate

$$L^{\infty}(\mathbf{Y}) = E\left[L|\{\mathbf{Y}\}\right] = \sum_{i=1}^{M} w_i N\left[\frac{N^{-1}(p_i) - r_i Y_{Sec(i)}}{\sqrt{1 - r_i^2}}\right]$$

is distributed according to the probability distribution of L where $\mathbf{Y}$ is distributed according to $N(\mathbf{0}, \sigma)$. In this setting, VaR or ES (expected shortfall) can be computed by Monte Carlo simulations generating random $\mathbf{Y}$s according to the above normal distribution. That is, the portfolio manager can measure the true value of portfolio risk if the manager knows the right sector $Sec(i)$ of borrower i for all i, and the true value of the parameters w_i, p_i, r_i, and σ for all i.

3 Mis-assignment of Borrowers

However, in practical conditions of risk management, the portfolio manager does not know some of them generally. The unknown values of them will be determined manually or by estimation from historical data of (proxies of) asset returns, and inevitably that process involves errors.

In this paper, we investigate the influence of incorrect determination of $Sec(i)$s, which represents the assignment of borrowers to the sectors, on estimation of the other parameters, and evaluate the influence on the portfolio risk computation. To evaluate the influence of the mis-assignment purely, we assume that the portfolio is infinitely fine-grained and that the portfolio manager correctly estimates the default probability p_is, that is, the manager knows the true value of p_is.

3.1 Condition 1: sector definitions are given

At first, let us assume that the portfolio manager knows the true σ but there is a possibility that the manager assigns some borrowers to wrong sectors. This assumption corresponds to a situation where the sector definition and correlation analysis among sectors are made by someone correctly in advance, but the manager might make mistakes of mis-assigning borrowers to wrong sectors.

Let $\bar{Sec}(i)$ denote the sector to which the manager assigns borrower i. If $Sec(i) = \bar{Sec}(i)$, borrower i is assigned to the right sector, but If $Sec(i) \neq \bar{Sec}(i)$, the borrower i is assigned to a wrong sector.

In this condition, the portfolio manager will determine the borrower i's factor loading r_i by estimating the correlation between X_i and $Y_{\bar{Sec}}(i)$. The true value of this correlation is $r_i \sigma_{Sec(i)\bar{Sec}(i)}$. The manager must estimate this value from historical data of X_i and $Y_{\bar{Sec}}(i)$. The accuracy of the estimation depends on the number of historical data n, and the average estimation error caused by statistical fluctuations has order $O(1/\sqrt{n})$. Here, to observe pure influences of mis-assignment of borrowers, let us assume that the manager has enough data $(n \to \infty)$ and the value $r_i \sigma_{Sec(i)\bar{Sec}(i)}$ can be estimated deterministically $(O(1/\sqrt{n}) \to 0)$, that is, the manager estimates the factor loading of the borrower i as $r_i \sigma_{Sec(i)\bar{Sec}(i)}$. Let us define the value as $\bar{r}_i$. ($\bar{r}_i = r_i \sigma_{Sec(i)\bar{Sec}(i)}$).

Then, the portfolio manager will measure the risk of the portfolio by computing the probability distribution of

$$\bar{L}^{\infty}(\mathbf{Y}) = E\left[L|\{\mathbf{Y}\}\right] = \sum_{i=1}^{M} w_i N \left[\frac{N^{-1}(p_i) - \bar{r}_i Y_{\bar{Sec}(i)}}{\sqrt{1-\bar{r}_i^2}}\right]$$

where $\mathbf{Y}$ is distributed according to $N(\mathbf{0}, \sigma)$.

Limit loss rate $\bar{L}^{\infty}$ differs from L^{∞} in the factor loadings and the following systematic factors. Since $\sigma_{SS'} \leq 1$, $\bar{r}_i \leq r_i$ holds. The factor loading estimated by the manager is not larger than the true value, and this leads to the possibility of underestimation of risk. In the section of Experiments, we will show that the mis-assignments generally cause underestimation of risk.

3.2 Condition 2: the manager defines sectors.

Next, let us assume that the portfolio manager defines sectors without knowing the true sector definition, and assigns the borrowers according to his own sector definitions.

Let K' be a number of sectors that the manager defined. Let $\hat{Sec}(i)$ denote the sector to which the manager assigned borrower i. We define several sets of borrowers as follows:

$$\begin{aligned} I[S, S'] &\equiv \{i|Sec(i) = S, \hat{Sec}(i) = S'\} \\ I[S, *] &\equiv \{i|Sec(i) = S\} \\ I[*, S'] &\equiv \{i|\hat{Sec}(i) = S'\}. \end{aligned}$$

The manager will define a composite systematic factor $\hat{Y}_S$ of sector S by $\hat{Y}_S \equiv \hat{y}_S/\hat{C}_S$, where $\hat{y}_S$ is the summation of X_is assigned to the sector;

$$\hat{y}_S = \sum_{i \in I[*,S]} X_i,$$

and $\hat{C}_S$ is a normalization factor to make $V[\hat{Y}_S] = 1$.

The manager must estimate $\hat{C}_S$ using historical data of $\hat{y}_S$. Also, according to the defined systematic factors, the manager must estimate the covariance between $\hat{Y}_S$ and $\hat{Y}_{S'}$ to compute the distribution of loss rate later. $\hat{C}_S$ should be the standard deviation of $\hat{y}_S$;

$$SD[\hat{y}_S] = \sqrt{\sum_{T=1}^{K}\sum_{T'=1}^{K} \sigma_{TT'} \sum_{j \in I[T,S]} \sum_{j' \in I[T',S]} r_j r_{j'} + \sum_{T=1}^{K} \sum_{j \in I[T,S]} (1 - r_i^2)},$$

and the true value of the covariance between $\hat{Y}_S$ and $\hat{Y}_{S'}$ is given by

$$\frac{\sum_{T=1}^{K}\sum_{T'=1}^{K}\sigma_{TT'}\sum_{j\in I[T,S]}\sum_{j'\in I[T',S']} r_j r_{j'} + \sum_{T=1}^{K}\sum_{j\in I[T,S]}(1-r_i^2)\mathbf{1}\{S=S'\}}{SD[\hat{y}_S]SD[\hat{y}_{S'}]}. \tag{1}$$

Let us assume that the manager has enough historical data, and these values can be estimated deterministically, that is, the manager estimates $\hat{C}_S$ as $SD[\hat{y}_S]$, and the covariance between $\hat{Y}_S$ and $\hat{Y}_{S'}$ as above. Let $\hat{\sigma}_{SS'}$ be this estimated covariance, and $\hat{\sigma}$ be the matrix of them.

Then, the portfolio manager will determine the factor loading r_i by estimating the correlation between X_i and $\hat{Y}_{\hat{Sec}(i)}$. For $i \in I[S,S']$, this correlation is given by

$$\frac{r_i\sum_{T=1}^{K}\sum_{j\in I[T,S']} r_j\sigma_{ST} + (1-r_i^2)}{SD[\hat{y}_{S'}]}.$$

Also, let us assume that the manager estimates the factor loading of the borrower i deterministically as above. Let $\hat{r}_i$ be this estimated factor loading.

Then, the portfolio manager will measure the risk of the portfolio by computing the probability distribution of

$$\hat{L}^{\infty}(\mathbf{Y}) = E\left[L|\{\hat{\mathbf{Y}}\}\right] = \sum_{i=1}^{M} w_i N\left[\frac{N^{-1}(p_i) - \hat{r}_i\hat{Y}_{\hat{Sec}(i)}}{\sqrt{1-\hat{r}_i^2}}\right]$$

where $\hat{\mathbf{Y}} = (\hat{Y}_1,\cdots,\hat{Y}_{K'})$ is distributed according to $N(\mathbf{0},\hat{\sigma})$.

In Condition 2, the estimated factor loading $\hat{r}_i$ generally differs from the true value $\bar{r}_i$ as it does in Condition 1. Moreover, the estimated probability distribution of the systematic factors $\hat{\mathbf{Y}}$ differs from the distribution of true systematic factors $\mathbf{Y}$ in Condition 2. Since the risk manager computes the risk of the portfolio using these estimated values, the computed risk is not equal to the true risk generally. In the section of Experiments, we will show that underestimation of risk occurs also in Condition 2.

4 Experiment

Here, we compute 99.9%-VaR of example portfolios under the above two conditions with several types of mis-assignment configurations. To express the configuration of mis-assignment, we introduce following variables;

$$Q(S,S') = |I[S,S']|/M \tag{2}$$

$$W(S,S') = \sum_{i\in I[S,S']} w_i, \tag{3}$$

and their matrixes

$$\mathbf{Q} = \begin{pmatrix} Q(1,1) & \cdots & Q(1,K') \\ \vdots & \ddots & \vdots \\ Q(K,1) & \cdots & Q(K,K') \end{pmatrix}, \mathbf{W} = \begin{pmatrix} W(1,1) & \cdots & W(1,K') \\ \vdots & \ddots & \vdots \\ W(K,1) & \cdots & W(K,K') \end{pmatrix},$$

where $Q(S,S')$ is the relative number of borrowers belonging to Sector S but assigned to Sector S', and $W(S,S')$ is the relative amount of principal of borrowers belonging to Sector S but assigned to Sector S'.

For simplicity, we assume that sector-wise homogeneity of the true model, that is, we assume that if $Sec(i) = Sec(j)$ then $p_i = p_j$ and $r_i = r_j$. However, note that the portfolio manager cannot utilize the homogeneity in the process of parameter estimation or sector definition because the manager does not know the true values of $Sec(i)$s.

4.1 Portfolio 1: two sectors

As a start point of this work, we assume a portfolio consisting of two sectors 1 and 2 in the true model[3] here. We assume that the factor loading $r_i = 0.5$ and the default probability $p_i = 0.5\%$ for all i, and five cases of the correlation of the systematic factor $\sigma_{12} = \sigma_{21} = 0.0, 0.2, 0.4, 0.6, 0.8$.

We consider three types of mis-assignment as follows:

Type 1 (Bias to Sector 1): Some borrowers in Sector 2 are assigned to Sector 1. We assume that

$$K = K' = 2, \mathbf{Q} = \mathbf{W} = \begin{pmatrix} 0.5 & 0 \\ 0.5e & 0.5(1-e) \end{pmatrix},$$

where e is mis-assignment rate.

Type 2 (Assignment to third Sector): Some borrowers in Sector 1 or 2 are assigned to Sector 3. Here, we assume that

$$K = 2, K' = 3, \mathbf{Q} = \mathbf{W} = \begin{pmatrix} 0.5(1-e) & 0 & 0.5e \\ 0 & 0.5(1-e) & 0.5e \end{pmatrix}.$$

We also assume that the correlation $\sigma_{13} = \sigma_{23} = \sigma_{12}$.

[3]Note that K might be greater than two. The assumption means $w(i) > 0$ for $i = 1$ or 2, and $w(i) = 0$ otherwise.

Type 3 (Mixture of Sector 1 and 2): some borrowers in Sector 1/2 are assigned to Sector 2/1. We assume that

$$K = K' = 2, \mathbf{Q} = \mathbf{W} = \begin{pmatrix} 0.5(1-e) & 0.5e \\ 0.5e & 0.5(1-e) \end{pmatrix}.$$

In all types of the mis-assignment, the model estimated by the portfolio manager falls into the true model when the mis-assignment rate e is 0. In Type 1 and 2, the estimated model with $e = 1$ falls in to one-factor model, and the estimated model with $e = 1$ falls in to the true model in Type 3 in Condition 2.

Figure 1, 2, and 3 respectively shows the computed 99.9%-VaR by Monte Carlo simulations with 100000 paths in the case where the true sector definition is given (Condition 1). Figure 4, 5, and 6 respectively shows the 99.9%-VaR computed similarly in the case where the portfolio manager defines the sectors (Condition 2).

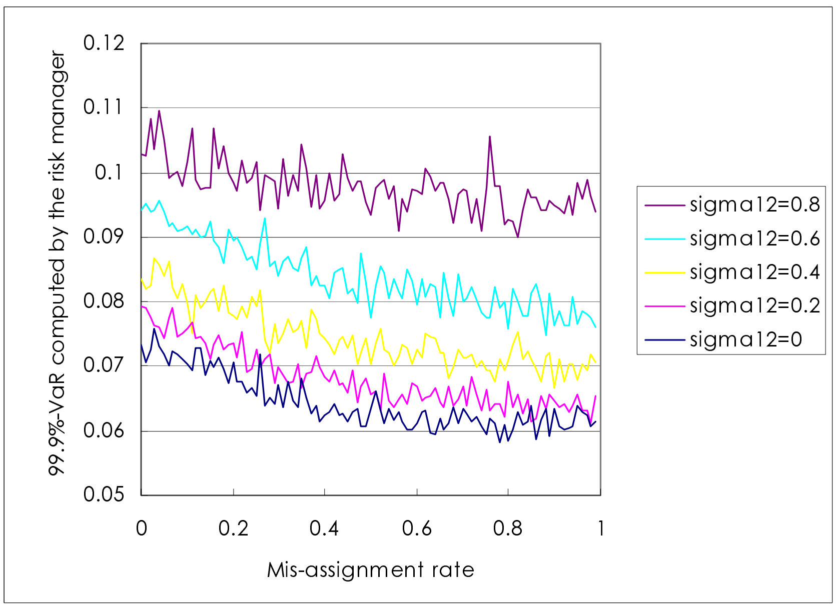

Figure 1: Computed VaR under Type 1 mis-assignment (Condition 1)

We can see that mis-assignment of borrowers leads to underestimation of concentration risk generally, and the amount of underestimation is larger under Condition 1 than that of Condition 2.

In Type 1 mis-assignment, Condition 1 and 2 seem to differ in the high range of correlation of the systematic factors. For example, with $\sigma_{12} = 0.8$, underestimation occurs under Condition 1 obviously, but it is negligible under Condition 2.

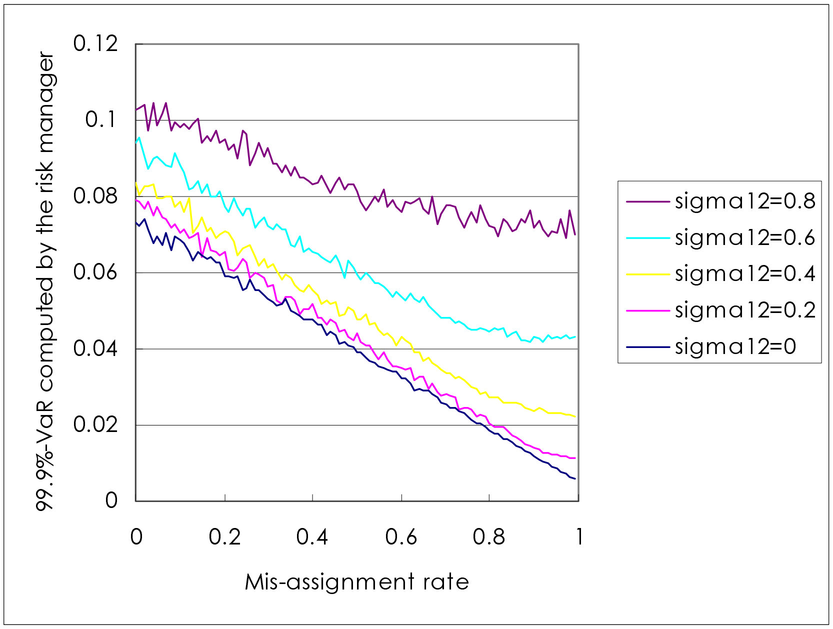

Figure 2: Computed VaR under Type 2 mis-assignment (Condition 1)

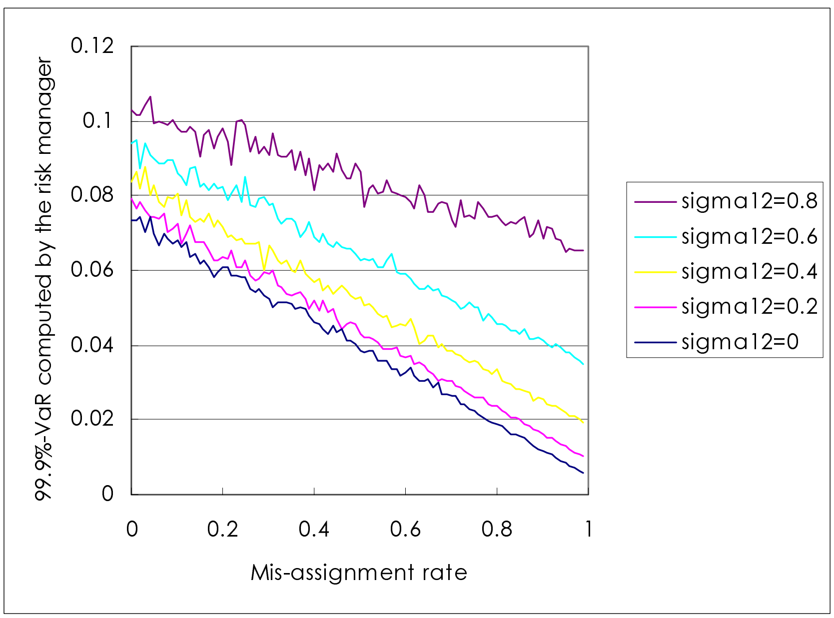

Figure 3: Computed VaR under Type 3 mis-assignment (Condition 1)

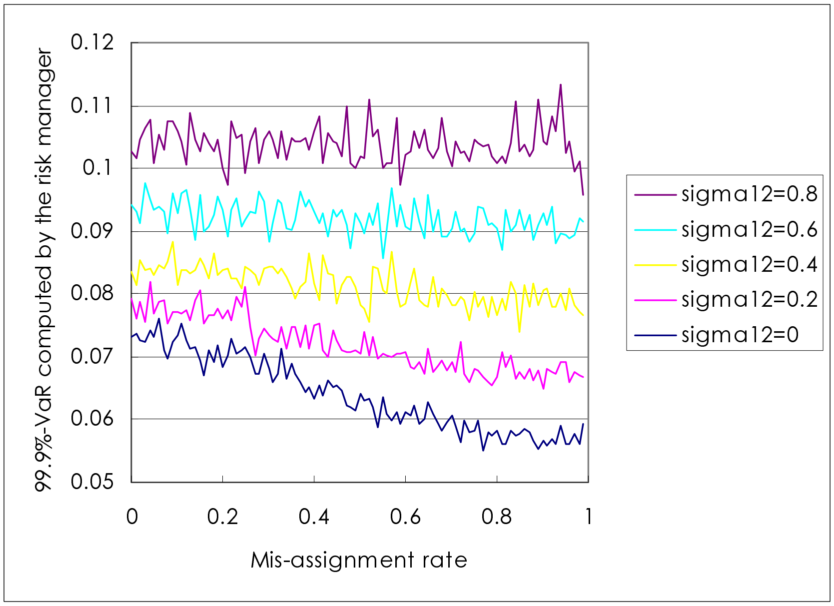

Figure 4: Computed VaR under Type 1 mis-assignment (Condition 2)

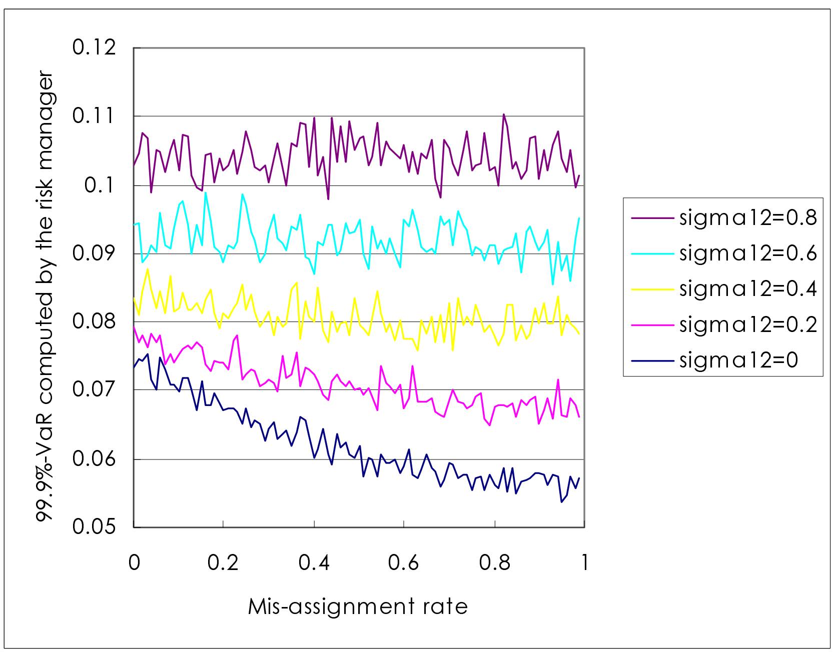

Figure 5: Computed VaR under Type 2 mis-assignment (Condition 2)

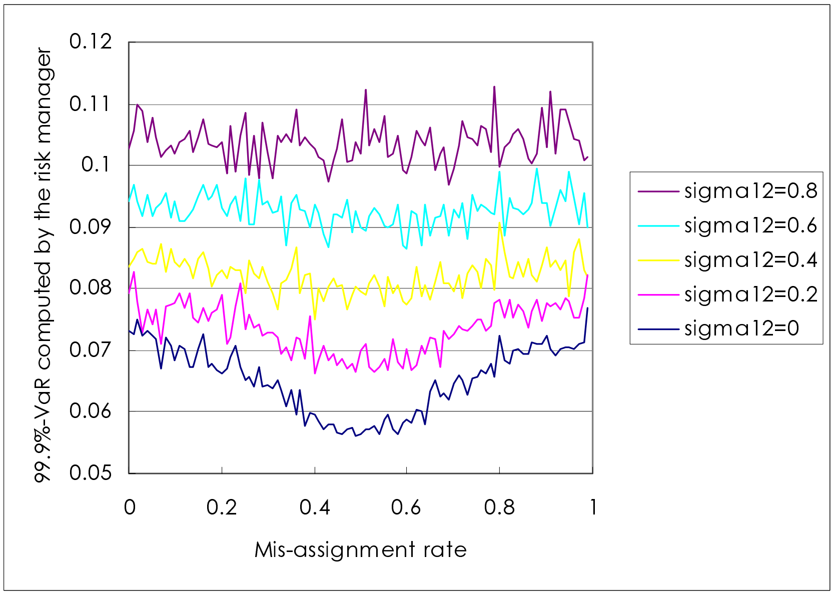

Figure 6: Computed VaR under Type 3 mis-assignment (Condition 2)

In Type 2 and 3 mis-assignment, serious underestimation of sector concentration risk are observed under Condition 1, where the portfolio manager uses the given sector definition. Though the underestimation under Condition 2 is much less than that under Condition 1, the amount of the underestimation reaches about 10% of the estimated risk at the mis-assignment rate $e = 0.1$ with low systematic correlation $\sigma_{12} = 0$.

We can also see that if the correlation σ_{12} of the systematic factor is larger than 0.4, underestimation of sector concentration risk does not occur practically under Condition 2 in all types of mis-assignment.

4.2 Portfolio 2: ten sectors

Here, we assume a portfolio consisting of ten sectors in the true model. We assume that the factor loading $r_i = 0.5$ and the default probability $p_i = 0.5\%$ for all i, and five cases of the correlation of the systematic factor $\sigma_{SS'} = 0.0, 0.2, 0.4, 0.6, 0.8$ where $S \neq S'$.

We consider three types of mis-assignment as follows:

Type 1 (Bias to Sector 1): Some borrowers in Sector 2 to 10 are assigned to Sector 1. We assume that

$$K = K' = 10, \mathbf{Q} = \mathbf{W} = \begin{pmatrix} 0.1 & 0 & 0 & \cdots & 0 \\ 0.1e & 0.1(1-e) & 0 & \cdots & 0 \\ \vdots & 0 & \ddots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \ddots & 0 \\ 0.1e & 0 & \cdots & 0 & 0.1(1-e) \end{pmatrix}.$$

Type 2 (Assignment to Sector 11): Some borrowers in Sector 1 to 10 are assigned to Sector 11. Here, we assume that

$$K = 10, K' = 11, \mathbf{Q} = \mathbf{W} = \begin{pmatrix} 0.1(1-e) & 0 & \cdots & 0 & 0.1e \\ 0 & \ddots & \ddots & \vdots & \vdots \\ \vdots & \ddots & \ddots & 0 & \vdots \\ 0 & \cdots & 0 & 0.1(1-e) & 0.1e \end{pmatrix}.$$

Type 3 (Mixture of ten sectors): some borrowers in each sector are assigned to other sectors. We assume that

$$K = K' = 10, \mathbf{Q} = \mathbf{W} = \begin{pmatrix} 0.1(1-e) & 0.1e/9 & \cdots & 0.1e/9 \\ 0.1e/9 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0.1e/9 \\ 0.1e/9 & \cdots & 0.1e/9 & 0.1(1-e) \end{pmatrix}.$$

In all types of the mis-assignment, the model estimated by the portfolio manager falls into the true model when the mis-assignment rate e is 0. In Type 1 and 2, the estimated model with $e = 1$ falls in to one-factor model.

Figure 7, 8, and 9 respectively shows the computed 99.9%-VaR by Monte Carlo simulations with 100000 paths in the case where the true sector definition is given (Condition 1). Figure 10, 11, and 12 respectively shows the 99.9%-VaR computed similarly in the case where the portfolio manager defines the sectors (Condition 2).

Qualitative behavior of underestimation in this portfolio is similar to that of Portfolio 1.

We can see that mis-assignment of borrowers leads to underestimation of concentration risk generally, and the amount of underestimation is larger under Condition 1 than that of Condition 2. We can also see that if the correlation $\sigma_{SS'}$ of the systematic factor is larger than 0.4, underestimation of sector concentration risk does not occur practically under Condition 2 in all types of mis-assignment.

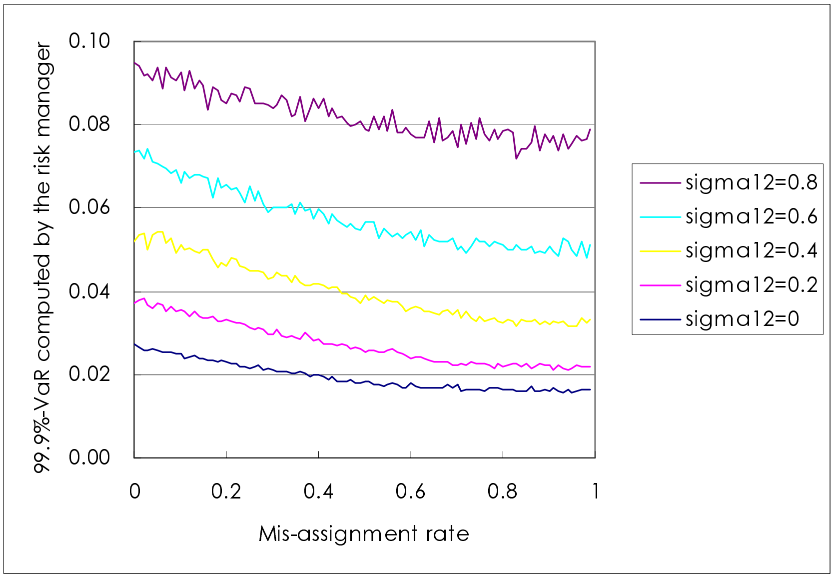

Figure 7: Computed VaR under Type 1 mis-assignment (Condition 1)

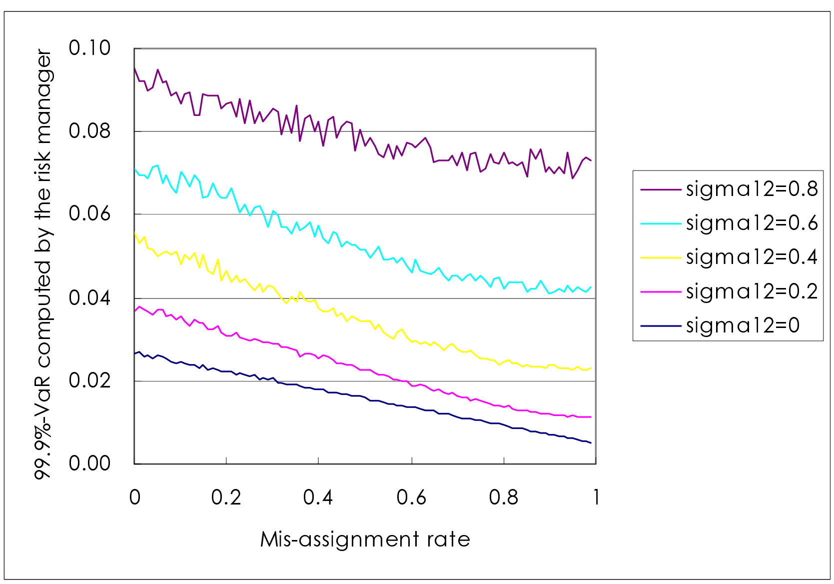

Figure 8: Computed VaR under Type 2 mis-assignment (Condition 1)

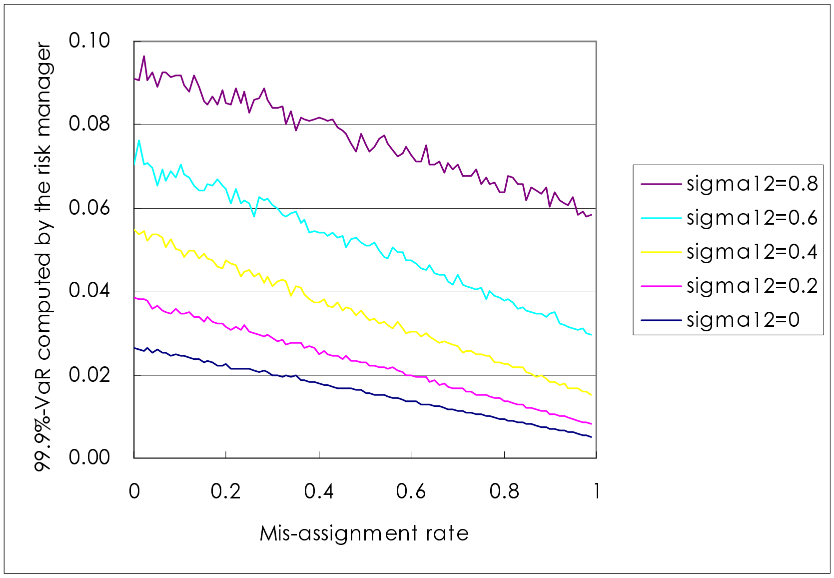

Figure 9: Computed VaR under Type 3 mis-assignment (Condition 1)

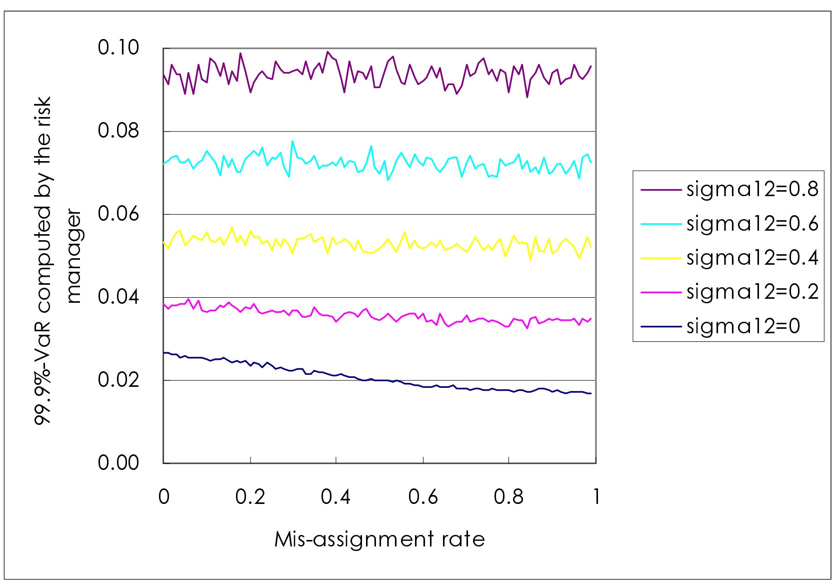

Figure 10: Computed VaR under Type 1 mis-assignment (Condition 2)

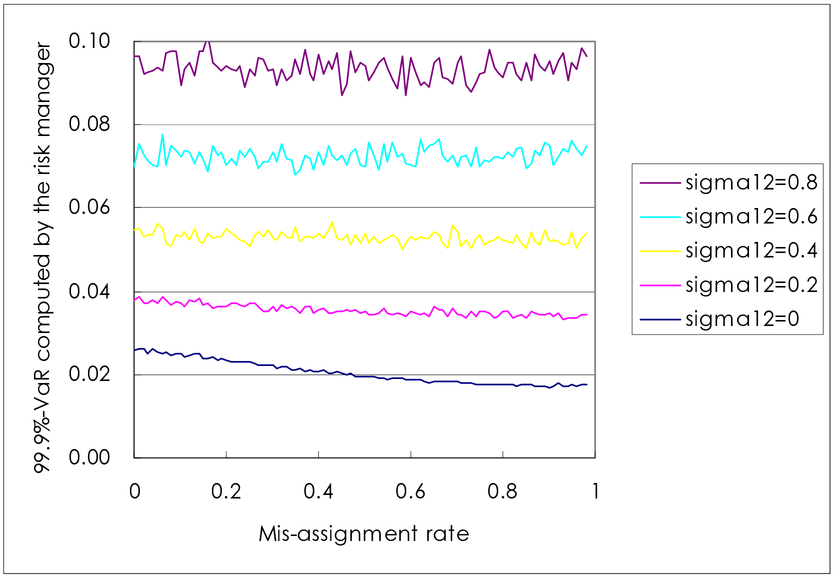

Figure 11: Computed VaR under Type 2 mis-assignment (Condition 2)

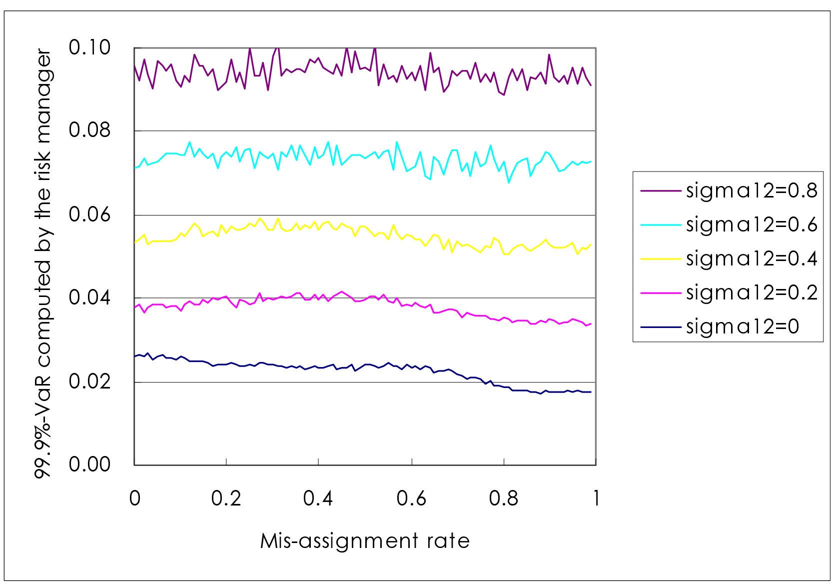

Figure 12: Computed VaR under Type 3 mis-assignment (Condition 2)

These results suggests that to reduce the amount of underestimation, a portfolio manager should define suitable sectors for the portfolio but not use previously prepared general sector definition intact. The results also suggest a possibility that the amount of underestimation might be negligible if the sector correlation is high enough.

5 Conclusion and future work

In this paper, we investigated underestimation of sector concentration risk caused by assigning borrowers to wrong sectors. We looked into two conditions of mis-assignment; 1) given sector definitions are used intact, and 2) sectors are defined by the portfolio manager. We derived the values of parameters which the portfolio manager will estimate, and compute 99.9%-VAR using the values. We observed that mis-assignment of borrowers generally leads to underestimation of the portfolio risk, and the amount of underestimation is generally larger under Condition 1 than that under Condition 2.

Evaluations of the influence of mis-assignment under following settings remain as future work; 1) finite granularity, 2) limited historical data, 3) using statistical model selection theories.

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