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Do Banks Purposely Diversify Loan Portfolios?

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Abstract

An empirical investigation is conducted on the determinants of loan portfolio structures based on data accumulated from 470 small Japanese banks during 2002-2003. Specifically, we analyze whether or not the banking organizations actively adjust the structure of their loan portfolios across borrowers' economic sectors in order to alter the variance of portfolio returns. The study leverages a unique dataset encompassing the banks' balance sheet data, as well as the characteristics of their lending opportunities in terms of availability and return variability. We find that, although adjusting portfolio structures across economic sectors can lead to a significant absolute change in the variability of portfolio returns, there is no evidence of the banks pursuing the benefits of inter-sectoral diversification when the structure of their loan portfolios is being determined. This and other findings of the study does suggest the banks face reduced benefits when adjusting their portfolio structures away from the structure of incoming loan applications, in comparison to the cost of such adjustment.

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I. Introduction

The notion of portfolio diversification – a strategy to diversify an asset portfolio across imperfectly correlated risk exposures in order to promote superior risk-return performance – has now become a great tenet of finance theory. This view is very influential in the area of bank management, where conventional wisdom (and bank regulators) generally treat high sectoral concentration of credit portfolios as a negative factor of bank performance. Unlike a market securities portfolio, however, choosing the sectoral structure of a bank loan portfolio is not necessarily a "free lunch", because the relative profitability of loans may depend on the choice of specific portfolio structure. The feature creates a controversy among both academicians and practitioners when considering if banks should pursue sectoral diversification of their loan portfolios. It also explains why it is not yet clearly established whether or not banks really do consider portfolio effects when adjusting the structure of their credit portfolios.

The question of whether banks should adjust their loan portfolios to achieve an optimal combination of both expected portfolio return and variance is far from being settled in the economic literature. Winton (1999) identifies two lines of theoretical argument: (1) the "financial institution view" suggests that portfolio diversification across industrial sectors and regions reduces the chance of costly financial distress and makes it cheaper for financial institutions to achieve credibility in their role as screeners and monitors of borrowers; (2) the "corporate finance view", however, argues that financial institutions (as any firms) should focus on a single line of business so as to take the greatest advantage of management expertise and reduce agency problems, leaving investors to diversify on their own.[1] The two views are divided in their implicit assumption about the level of cost associated with portfolio adjustment by financial institutions. The former one assumes the cost is small and the latter it is significant.

Deciding between the two views requires empirical investigation. The empirical literature, however, delivers mixed signals because the portfolio effects of diversification are not directly observable. The general approach used in the empirical studies is to determine whether an expanded reach of a bank to multiple

[1] The former view was formalized by Diamond (1984) and Boyd and Prescott (1986) among others, and the latter one can be traced to Jensen (1986). A similar divide can also be observed in the applied banking literature, in which risk management sources (e.g. Bessis, 2002) devote chapters to the portfolio risk issue, and general bank-management sources (e.g. Kosh and MacDonald 2002) are more focused on managing stand-alone loans.

industries, geographic regions and financial activities is associated with its improved risk-return performance. The literature has reached agreement that there is some risk reduction from business combinations of banking with other financial activities, especially with life insurance (Rose 1989, Templeton and Severiens 1992, Boyd et al 1993, Allen and Jagtiani 2000, Laderman 2000, Estrella 2001), but it disagrees on whether geographic and sectoral diversification helps to reduce risk. Liang and Rhoades (1988), Rose (1996) Rivard and Thomas (1997), Hughes et al (1998), Gunther and Robinson (1999), Acharya et al (2002), Shiers (2002), Meon and Weill (2005) have found that extending bank activities across different regions (with different sectoral structures) does, in fact, lead to potential or actual reduction in volatility risk and insolvency risk, whereas DeLong (2001), Ismail and Davidson (2005), Carlson and Mitchener (2005) have suggested weak, or no benefits, from such diversification. Two studies have explored the problem in the case of small banks: Emmons et al (2004) studied hypothetical mergers of US community banks and have found the idiosyncratic risk (the risk of lending to too few customers in too few industries) to dominate the local market risk (the risk of lending concentration in too few regions). They concluded that the greatest risk reduction benefits are achieved primarily by increasing a community bank's size and not necessarily by its geographic diversification. Stiroh (2004) focused when evaluating the effect of diversification across different activities vs. across different borrowers on the risk-adjusted performance of community banks and suggests diversification benefits in the latter case only.

Besides obvious differences in testing methodology and data, the mixed results are arguably related to the following four problems of the empirical setup. First, testing diversification by the dynamics of banks' profits or equity prices may not permit controlling for variations in the risk-taking behavior that occur due to the diversification. As found by Demsetz and Strahan (1997), Acharya et al (2002), Cebenoyan and Strahan (2004), Casu and Girardone (2004), more diversified banks also tend to take more risks.

Second, even without changes in risk-taking, the testing approach may not permit a complete detangling of the portfolio effects of diversification from its other effects. The synergy and market-power benefits may give bank managers additional room for discreetly adjusting reported earnings, and thus possibly causing further reduction in volatility risk measures beyond the pure portfolio effect.

Third, the results may be biased because reduced credit concentration *per se* does not necessarily lead to reduced variability, especially in the case of small banks.

As suggested by Emmons et al (2004), increasing the number of loan customers in a bank's portfolio can produce a stronger diversification effect than increasing the number of local markets covered by the portfolio. Hence, if a portfolio is being diversified by its simple reallocation across multiple market exposures, such diversification may not reduce, but to the contrary, increase its return volatility.

Finally and, we believe, most importantly, the empirical setup of the previous studies does not allow testing the degree to which banks purposely use the diversification effect: The observed credit concentration rates do not necessarily reflect the banks' portfolio choices, but simply the structure of loan demand the banks face in their market segments. Or, their expansion to new geographic regions may also be driven by other considerations unrelated to the issue of portfolio diversification. Confirming the fact that banks do purposely use the diversification effect is knowledge of pivotal importance because one cannot conclude that loan portfolio diversification is beneficial for banks simply on the basis of reduced volatility of portfolio returns; one needs to account for the cost of diversification, although it is typically not observable.

This study approaches the empirical problem from a new direction. In particular, we examine whether the observed sectoral structure of bank loan portfolios is influenced by the portfolio effect. Our null hypothesis is that, after controlling for the sectoral structure of loan demand, factors related to the portfolio variance have no significant effects on the observed sectoral portfolio weights, and the alternative hypothesis is that the effects are significant and mutually consistent. This formulation helps to avoid, at least, three of the above mentioned problems. Furthermore, we focus on the portfolio structures of small banks that, arguably, have little access the alternative tools of portfolio risk management like loan sales and credit derivatives.

Using a new large dataset of Japanese small banks, the study finds that, although adjusting portfolio structures across borrowers' economic sectors can lead to a significant absolute change in the variability of portfolio returns, there is no evidence indicating that the banks are actually pursuing the benefits of (inter-sectoral) diversification when they decide the structure of their loan portfolios. By comparison, we find a strong effect on the loan portfolio structures of small banks from the structure of the local loan demand. When taken together, these two findings suggest that the banks face reduced benefits of adjusting their portfolio structures away from the structure of incoming loan applications in comparison to the cost of such adjustment.

The rest of the paper is organized as follows. The next section develops a simple model of loan portfolio choice. Section III describes the process of data

collection, properties of the dataset, and empirical setup. Section IV reports and discusses estimation results, and Section V concludes. Appendices I and II give further details of the model and the dataset.

II. The model

In this section, we follow the portfolio model approach[2] and assume that banks behave as portfolio managers, i.e. (1) they take prices (returns) as given and (2) choose financial assets so to maximize the expected utility of the bank's financial wealth. For simplicity sake, we particularly focus on the case of a concave utility function and the Gaussian distribution of financial asset returns. The assumptions imply first that the banks are risk averse to some degree. The view can be justified by the argument that with the separation of the management and ownership functions in bank governance their behavior reflects the utility of the management who can be risk averse (Jensen and Meckling 1976) - or that the owners of the banks can also be risk averse – especially in the case of those small institutions which are organized as mutual credit societies and essentially owned by their depositors. The assumed Gaussian (normal) distribution of asset yields can be justified by the observation that unlike distributions of individual loan exposures, which are typically skewed to the left, distributions of loan portfolios are more or less symmetric. The assumptions, however, yield significant simplifications as they enable one to describe asset choice by the first two moments of return distributions and make the variance effects of portfolio choice more tractable.

Furthermore, to bring the model closer to reality we also assume that, for some reason,[3] the funding cost that the bankers pay on their deposits does not fully reflect their assumed risks. Under limited liability, the assumption implies that the risk-taking behavior of bankers can change depending on the level of their own wealth at stake.[4] To see the effect, we first develop a model of bank behavior under full liability and then extend it to the limited liability case.

Portfolio choice under full liability

As a basic setup, we consider a bank that chooses an optimal combination of assets by simultaneously maximizing portfolio return and minimizing its variance. The market pricing of loans is assumed to reflect their return variability, (market-)

[2] See, e.g., Kim and Santomero (1988).
[3] Either because of fixed deposit insurance premiums, or severe information asymmetries, etc.
[4] See Rochet (1992).

average advantage (disadvantage) for the purpose of portfolio diversification, and (market-) average monitoring and credit cost. The bank is currently operating only in a segment of the market, so that the sectoral structure of loan applications it faces differs from that reflected in the market pricing of loans. Hence, the bank can attain an improved mean-variance combination by diversifying the structure of its portfolio away from the structure of incoming applications.

To incorporate these features, we start with a simple one-period setup: A bank exists over one period and makes portfolio decisions at its beginning in order to maximize its expected wealth at the end. The bank invests all its own and depositors' funds in loans, and its wealth at the end (W_1) is the difference between the value of its asset portfolio (Q_1) and the amount promised to be paid to the depositors ($D = (1-k)Q_0$). The portfolio's value at the end is driven by its expected return E_{rQ} ($=Q_1-Q_0$) and variance σ^2_Q. By full liability, the portfolio moments can be directly used to describe the moments of the bank's wealth:

[1] $E_W = Q_1 - D = kQ_0 + E_{r_Q}$ and $\sigma_W{}^2 = \sigma_Q{}^2$.

Based on the assumptions above, the expected utility (U) of the wealth maximizing bank can be specified as:

[2] $U = E_W - \frac{1}{2}A\sigma_W{}^2 = kQ_0 + E_Q - \frac{1}{2}A\sigma_Q{}^2$,

where A is a risk aversion coefficient. The bank maximizes its utility by choosing an optimal allocation weights (λ_i, $\sum_1^n \lambda_i = 1$) for by-industry sub-portfolios within Q_0. Then,

[3] $E_Q = Q_0 \sum_1^n \lambda_i E_{r_i}$

[4] $\sigma_Q{}^2 = Q_0{}^2 \left(\sum_{i=1}^n \lambda_i{}^2 \sigma_i{}^2 + 2\sum_{i=1}^n \sum_{j=1}^n \lambda_i \lambda_j \rho_{i,j} \sigma_i \sigma_j \right), \quad i \neq j$,

where E_{ri} is the expected (net) rate of return of the i-th industry sub-portfolio, σ_{ri}^2 – its variance, and $\rho_{i,j}$ – return correlation between the i-th and j-th sub-portfolios.

Initially, the bank receives an inflow of qualifying applications of size Q_0. Among them a_iQ_0 ($\sum_1^n \alpha_i = 1$) belong to the industry in question. Similarly to the setup of Ho and Saunders (1981), the bank accepts all the arriving applications but tries to adjust their allocation across industries indirectly – by setting markups (a_i) on the gross interest rates (R_i) it charges on the loans:

$$R_i = \overline{R}_i + a_i ,$$

where R_i-bar is the "true" (market) loan rate for the i-th industry. Hence, in this setup the bank faces the task of finding a combination of λ_i and a_i which maximizes its wealth. For simplicity sake, however, we also assume that the bank possesses perfect knowledge of the loan demand schedule (demand elasticity coefficients, β_i) in its market segment. And if λ_i and a_i are related as:

$$\lambda_i = \alpha_i - \beta_i a_i \quad ,$$

the number of maximization variables effectively declines to n.

The bank pays several types of cost on its lending. Besides the interest rate on deposits (included in D), it also faces industry-specific credit cost, monitoring cost, and operational (overhead, etc.) cost. The bank tries to keep its credit cost in line with the industry-average level by hiring new credit officers who possess monitoring expertise the bank lacks, and displacing existing staff with less demanded monitoring expertise. Since the structure of monitoring know-how is explained by lending activities before the date, diversification to new markets leads to such additional staff-reallocation cost.[5] Now, letting r_i denote the market interest rate net of all credit, operating, and monitoring cost, the expected net rate of return (E_{ri}) becomes:

$$[5] \quad E_{r_i} = R_i - \{\text{cost}\}_i + a_i = r_i - c_a \frac{\lambda_i - \lambda_{0i}}{\lambda_i} + \frac{\alpha_i - \lambda_i}{\beta_i},$$

where c_a denotes the unit rate of the staff reallocation cost and λ_{0i} – the initial endowment of staff experienced in the i-th industry ($\sum_1^n (\lambda_i - \lambda_{0i}) = 0$).

In order to describe the effect of diversification on the portfolio variance, we distinguish between diversification across industries and diversification across geographic regions. For simplicity sake, the two effects are assumed to be independent of one another, with the latter one simply reducing the total size of the portfolio variance σ^2_Q by some factor g ($0<g<1$). The variances of industry sub-portfolios (σ_{ri}^2) are related to the industry-specific levels of return variability (σ_i) and to the number of stand-alone loan exposures included in each sub-portfolio (N_i). In particular, we assume that

[5] Following the arguments of Cerasi and Daltung (2000) and Berger et al (2005), one may suggest that geographic diversification can also bring operational deficiencies. While admitting this possibility we ignore it in the model setup because this cost would be independent of λ_i. Furthermore, the model also ignores the effect of spreading fixed monitoring costs across larger sub-portfolios. The feature can be justified by the fact that λ_i would be influenced only by the difference between the fixed cost in industry i and the weighted average of that in other industries, which should not be large.

$$[6] \quad \sigma_{r_i} = \sigma_i \left(1 + \frac{1}{N_i}\right) = \sigma_i \left(1 + \frac{\gamma_i}{\lambda_i Q_0}\right),$$

where γ_i are industry-specific average sizes of stand-alone exposures.

Given the assumed utility function and imperfect correlation of returns in the loan portfolio, one can show that the maximization problem has a unique set of solutions for portfolio weights λ_i. This is the standard result for the portfolio choice problem within the mean-variance framework, in which the choice of the optimal allocation weight for an industry sub-portfolio is governed by the tradeoff between expected return maximization and variance minimization. There should be no strict corner solutions when λ_i^* take on 1 or 0. The optimal weight may still be very close to either of the two extremes. It could be so, for example, if there are both low elasticity of demand (small β_i) and low risk aversion (small A), while a_i remains close to 1 or 0; or, if risk aversion is high (large A) but the portfolio size (Q_0/γ_i) is small.

The purpose of this modeling exercise, however, is to highlight the intuition that the choice of λ_i is driven by the *relative* characteristics of by-industry sub-portfolios. To this end, we express the optimal weight of sub-portfolio 1 (λ_1^*) in terms of the optimal weights of other sub-portfolios (λ_2^*, … λ_n^*). In particular, having plugged [3]~[6] into [2], we differentiate U with respect to λ_1, assuming that an incremental increase of λ_1 leads to a proportional reduction of all other weights. Then, normalizing Q_0 to 1 and solving $\partial U/\partial\lambda = 0$ for λ_1 yields:

$$[7] \quad \lambda_1^* = \frac{R_{d1} - 2c_a + P_{d1} - B + Ag\left(\sigma_1^2 - S_{d1} + V - 2V_{d1} - G_{d1}/2\right)}{2/\beta_1 + Ag\left(\sigma_1^2 - 2V\right)},$$

where the terms with a "d" subscript are defined as follows ($\{i, j\} = 1,...n, \ i \neq j$):

$$R_{d1} = r_1 - \left(\sum_{i=2}^{n} \lambda_i^* r_i\right) \Big/ \left(\sum_{i=2}^{n} \lambda_i^*\right)$$

$$P_{d1} = \frac{\alpha_1}{\beta_1} - \left(\sum_{i=2}^{n} \lambda_i^* \frac{\alpha_i}{\beta_i}\right) \Big/ \left(\sum_{i=2}^{n} \lambda_i^*\right)$$

$$B = \left(\sum_{i=2}^{n} \frac{\lambda_i^{*2}}{\beta_i}\right) \Big/ \left(\sum_{i=2}^{n} \lambda_i^*\right)$$

$$S_{d1} = \sigma_1^2 - \left(\sum_{i=2}^{n} \lambda_i^{*2} \sigma_i^2\right) \Big/ \left(\sum_{i=2}^{n} \lambda_i^*\right)$$

$$V = \left(\sum_{i=2}^{n} \lambda_i^* \rho_{1,i} \sigma_1 \sigma_i \right) \Big/ \left(\sum_{i=2}^{n} \lambda_i^* \right)$$

$$V_{d1} = V - \left(\sum_{i=2}^{n} \sum_{j=2}^{n} \lambda_i^* \lambda_j^* \rho_{i,j} \sigma_i \sigma_j \right) \Big/ \left(\sum_{i=2}^{n} \lambda_i^* \right)$$

$$G_{d1} = \sum_{i=1}^{n} \gamma_i \left(\rho_{i,1} \sigma_i \sigma_1 - \left(\sum_{j=2}^{n} \lambda_j^* \rho_{i,j} \sigma_i \sigma_j \right) \Big/ \left(\sum_{j=2}^{n} \lambda_i^* \right) \right)$$

From [7] we see that λ_1^* is driven by relative differences between sub-portfolio 1 and the rest of the lending portfolio. First we observe that, for a portfolio with perfect diversification of stand-alone exposures, the second term in S_{d1} is a weighted average of all the diagonal elements of its variance except σ_1^2. Hence, λ_1^* is, obviously, a decreasing function of the relative return variability (S_{d1}).

Similarly, V is a weighted average of the off-diagonal elements belonging to the first row and column of the portfolio variance, and the second term of V_{d1} is a weighted average of all other off-diagonal elements. Besides being influenced by the level of return variability, these elements also reflect return correlations. Accordingly, [7] suggests that the optimal weight λ_1^* is a decreasing function of the difference between the average return correlation of sub-portfolio 1 vis-à-vis other sub-portfolios and the average return correlation among the other sub-portfolios.

G_{d1} reflects the relative effect of imperfect diversification of stand-alone exposures. In this expression, the average loan size in each industry (γ_i) is multiplied by the difference between the first element and the weighted average of other elements in the corresponding row of the portfolio variance. Noting that the diagonal elements of the variance are typically larger than its off-diagonal elements, we see that the difference is likely to be positive in the first row and negative in all other rows. Hence, λ_1^* declines (G_{d1} increases), as the difference between γ_1 and $\{\gamma_2 \ldots \gamma_n\}$ becomes larger.

Expression [7] also suggests that the optimal weight λ_1^* is an increasing function of the relative profitability of sub-portfolio 1 (R_{d1}) and of the industry's relative share in the local loan demand (P_{d1}). The effect of the geographic concentration (g), however, is uncertain as its sign depends on the relative size of the diagonal vs. off-diagonal elements, in addition to depending on the optimal weight itself.

In sum, the model predicts that the structure of a bank's loan portfolio will systematically deviate from that of the local loan demand because of factors related to both portfolio return and variance. The bank is likely to emphasize lending to an

industry beyond its share in incoming loan applications, when (1) it promises higher return than other sectors, (2) the reallocation cost of loan-monitoring staff is low, (3) the interest rate elasticity of the loan demand is high, (4) its return variance is smaller than on average in the other sectors, (5) its average return correlation vis-à-vis the other sectors is small compared to the average return correlation among the other sectors, (6) its average loan size is small compared to that found in other sectors. As discussed below, under limited liability the bank may turn its portfolio selection policy to variance-maximization and the signs of the variance-related effects (4)~(6) may be reversed. Still, the signs should be consistent across different industries. Therefore, alternating (unstable) signs of the variance effects will indicate reduced benefits of inter-industry diversification for banks.

Portfolio choice under limited liability

Under limited liability, a bank's wealth cannot be negative. The restriction implies that one should use the truncated (from-below) moments of Q_1 to describe W_1. In particular, by the assumption of the Gaussian return distribution, we write

[1′] $E_W = kQ_0 + E_{r_Q} + \sigma_Q h[X]$ and $\sigma_W{}^2 = \sigma_Q{}^2\left(1 - \frac{h[X]}{h[X] - X}\right)$,

where $X = (D - Q_1)/\sigma_Q = -(kQ_0 + E_{rQ})/\sigma_Q$ is the standardized truncation point (or "distance to the bank's default") and $h[X]$ is the Gaussian hazard function defined as $h[X] = \phi[X]/(1-\Phi[X])$ with $\phi[X]$ and $\Phi[X]$ denoting the normal pdf and cdf correspondingly. Now, the utility becomes:

[2′] $U = kQ_0 + E_{r_Q} - \frac{1}{2}A\sigma_Q{}^2 H$,

where

$$H = 1 - \frac{h[X]}{h[X] - X} - \frac{2h[X]}{A\sigma_Q}$$

From the properties of $h[X]$, we see that $\partial U/\partial\sigma_Q$ changes its sign from minus to plus as X declines to 0.[6] It means that depending on the degree of its risk aversion and the level of asset return uncertainty, a utility maximizing bank changes its portfolio policy: It minimizes the portfolio variance when performing at a high level of capital adequacy (high rate of asset return), but turns to variance maximization when at a low level of capital adequacy (low rate of asset return). To illustrate the behavior change, one can consider a bank choosing which asset to include in its portfolio. If there are two available assets of the same expected yield and variance but different

[6] Appendix I provides further details of the result.

correlation with the existing portfolio, the bank would reduce the portfolio's variance by choosing one with low correlation and would increase it by choosing another with high correlation. Since both assets would contribute with the same yield, the choice between them is likely to depend solely on the resulting change in the portfolio variance and thus on the bank's capital adequacy.

The observed change in portfolio selection policy alters the model in two important ways. First, it suggests that the signs of some partial effects of λ^* may change depending on the relative levels of (kQ_0+E_{rQ}) and σ_Q. Second, it may also drive the optimal allocation weight λ_i^* away from the solution of $\partial U/\partial\lambda = 0$. To see the effects we write:

$$\frac{\partial U}{\partial \lambda} = \frac{\partial E_Q}{\partial \lambda} - \frac{1}{2} Ag \left(\frac{\partial \sigma_Q^{\ 2}}{\partial \lambda} H + \frac{\partial H}{\partial \lambda} \sigma_Q^{\ 2} \right) = 0$$

Direct solving yields involved expressions, but the implications of H can be demonstrated by solving in terms of the existing variance level (σ_{Q0}^2):

$$\frac{\partial U}{\partial \lambda} \approx \frac{\partial E_Q}{\partial \lambda} - \frac{1}{2} Ag \frac{\partial \sigma_Q^{\ 2}}{\partial \lambda} [H] = 0$$

and

$$[7'] \quad \lambda_1^{\ *} \approx \frac{R_{d1} - 2c_a + P_{d1} - B + [H]Ag\left(\sigma_1^{\ 2} - S_{d1} + V - 2V_{d1} - G_{d1}/2\right)}{2/\beta_1 + [H]Ag\left(\sigma_1^{\ 2} - 2V\right)},$$

where $[H] = H + \dfrac{\partial H}{\partial \sigma_Q^{\ 2}} \sigma_{Q0}^{\ 2}$.

Obviously the expression in brackets ([H]) appears in all the partial effects of λ^*. Since it turns negative for some combinations of A and X, the feature suggests that the signs of the partial effects will vary depending on the levels of capital adequacy, return variability, and risk aversion.[7] By the same logic, however, the second derivative $\partial^2 U/\partial\lambda_i^2$ turns positive for some A, k, E_{rQ}, and σ_Q, and the optimal allocation weight becomes a corner solution with λ_i^*=1 if $U_{\lambda=1}$–$U_{\lambda=0}$>0, and λ_i^*=0 otherwise. Noting that for the return-related partial effects (those of R_{di}, c_a, P_{di}, and B) the value of [H] at which

[7] By direct differentiation,

$$[H] = 1 - h[X]\left(2\frac{1/\sigma_Q - 1 - X(h[X] - X)}{A} + \frac{h[X](1 + \sigma_Q X^2) - X(1 + \sigma_Q(1 + X^2))}{(h[X] - X)^2} \right).$$

We see that the multiplication factor of the second term (in parentheses) becomes strictly positive when σ_Q is around 1 and below. Hence, a sufficiently low A will drive the entire second term above 1.

they should change sign coincides with that at which the corner solutions start dominating ($[H]= -2/[\beta_i Ag(\sigma_i^2 - V_i)]$), we see that the observed signs of these variables will not be affected by a bank's solvency. The signs of the variance-related partial effects (those of A, g, σ_i^2, S_{di}, V_i, V_{di}, G_{di}) become reversed when $[H]$ is on the interval from 0 to $-2/[\beta_i Ag(\sigma_i^2 - V_i)$, and remain reversed over the corner solution range ($[H]<-2/[\beta_i Ag(\sigma_i^2 - V_i)]$). Hence the observed signs of the variance-related variables will switch once as the bank's solvency declines.

In sum, the model suggests that under limited liability the portfolio selection policy of a bank may be in two modes, depending on the levels of capital adequacy, asset return / variability, and risk aversion. First, the bank may be allocating its funds among industries in order to minimize the total variance through diversification (while maximizing expected return). Second, the bank may be either allocating all its funds to a single industry in order to maximize the portfolio variance. Or, it may be a "variance-maximizer" but still choosing a mix of several industry sub-portfolios because it gives a better variance-return combination than a single-industry portfolio. An obvious implication of the result for the following empirical analysis is that the observed portfolio weights of banks may be non-linear in the variance-related factors, and thus the banks' solvency needs to be properly controlled for in the empirical model and estimation approach.

III. Data and Empirical Setup

To test the model empirically we build a large set of data related to small business lending by Japanese banks. Unlike balance sheet information, data on the bank-specific loan demand structure and credit cost variability are not readily available and thus need to be estimated. In preparing the data we proceed in two basic steps – first, collecting (estimating) relevant information by geographic region, and then translating it to bank-specific figures by applying geographic exposure weights for each bank.

The estimates draw extensively on the small business (SME) loan data collected in the Credit Risk Database (CRD).[8] We use its data file of March 2003, which contains more than 4 million records of 1 million strong small businesses that had

[8] The CRD project is run by the CRD Management Council under the auspices of Japan's Ministry of Economy, Trade, and Industry (METI). It collects balance sheet and default data of SMEs anonymously supplied by its members – semi-public credit guarantee associations and private banks. In return, the members receive regular updates of a SME credit score model developed by the Council. By the date, the CRD project has been the most successful effort in collecting statistical data about Japanese SME borrowers.

borrowed from banks in 1995-2002. For bank-specific information we rely on the accounting and branch-distribution data available from the Keio Banking Database (KBD). Its data file covers Japan's small banking organizations – credit associations (*shinkin* banks) and credit cooperatives over 1989-2004. Information about commercial banks is drawn from the Nikkei NEEDs file.

This study employs banking data for 2002 and 2003 business years. In particular, we focus on banking organizations specializing in SME lending – the credit associations and cooperatives and the commercial banks belonging to the Second Regional Bank Association. After removing some observations arguably distorted by M&As and restrictive charters,[9] the (two-year) combined number of observations in our sample totals 851.

Drawing on these sources we construct a data set tailored to the needs of this study.[10] The dependent variable $LAMBDA_i$ is defined as the observed share of loans to the *i*-th sector in the credit portfolio of a bank at the end of a business year (March 2003 or March 2004). We consider 7 large domestic sectors: manufacturing, construction, transport and communication, wholesale and retail trade, real estate, services, and other. The combined share of these sectors and household lending sums to unity. Lending to public entities is treated as trivial risk exposure and therefore excluded.

$ALFA_i$ is a proxy of the loan demand by SMEs faced by the bank in the local lending markets it operates in. It records shares of the 7 economic sectors estimated from the previous year's data.

As a measure of the geographic reach of the bank, *DIST* we employ the weighted average physical distance between its employees at the end of the previous year. The measure increases as the bank allocates a larger share of its labor force to more distant branch offices.

DtD denotes a measure of the bank's insolvency risk, assessed from portfolio variability estimates and mid-year accounting data. It is calculated as the number of standard deviations of portfolio return covered by the bank's own funds. This metric

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[9] Japan's credit associations and cooperatives are organized as mutual credit societies. This legal status implies that they act for the mutual benefit of their members (who are both their depositors and borrowers) and should not necessarily seek profit in their activities. Still, over the course of the nation's postwar development, the credit associations and the vast majority of the cooperatives have made their membership open to anyone within their business areas and thus have effectively grown into local savings banks. Furthermore, our data sample excludes all the credit cooperatives, which membership is limited to specific occupations or places of employment. Hence, one may argue that the theoretical results of the previous section are applicable to all small banks in our dataset, regardless of their legal status.

[10] Appendix II give a full record of the data construction procedures used.

is adjusted to account for the presence of bank assets other than loans.[11]

$GAMMA_i$ gives the difference between the prevailing size of a stand-alone loan exposure in the *i*-th sector and the average of prevailing exposure sizes across the rest of the portfolio, divided by a mid-year estimate of the loan portfolio size of the bank in yen million.

Similarly, VAR_i stands for the difference between the variances of credit cost of loans in the *i*-th sector and of loans in the rest of the portfolio on average, and RHO_i for the difference between the average correlation of the *i*-th sector's credit cost vis-à-vis other sectors and the average correlation among the other sectors. As a primary data input, both variables use credit cost variability estimates (for 1-year loans) averaged over a 3-year period prior to the year of $LAMBDA_i$.

Table 1 reports the descriptive statistics of the data divided by the three types of banking organizations present in the sample. The three groups exhibit clear differences in their positioning in local lending markets. By the median size of credit portfolios, an average credit cooperative is 38% of an average credit association and only 6% of a regional bank. Still we see that the geographic reach of the cooperatives is on average the same as that of the associations. The feature reflects the fact that the cooperatives are smallest institutions with a few branch offices dispersed over relatively large regions. By comparison the office network of the credit associations has more than doubled density and, thus, this group is in much closer contact with the characteristics of local markets. The commercial banks have even more sparse office networks and tend to accommodate loan demand from the largest SMEs. Hence, the business environment the commercial banks face should be in much poorer correspondence with the local market characteristics. Since in this study we proxy the bank-specific business environment according to the economic characteristics of municipalities, where the banks locate their offices, the lending policy of credit associations naturally becomes the focus of our interest. Furthermore, the three groups of banking organizations are clearly different in their "distances to default" with the associations being more solvent and conservative. Considering these and

[11] The adjustment procedure effectively assumes that all the other assets do not produce any losses the bank's own funds should offset. Although the assumption is questionable in general, it seems to well reflect the loss exposure of the small banks included in our dataset: On average, their loan portfolio covered 55% of the total assets; the securities portfolio accounted for 22%; and the rest (23%) was in the form of cash reserves, money market lending and fixed assets. Considering, however, that 35-40% of the securities portfolio was invested in public debt and that for FY 2002-2003 the prospects of interest rate increases were bleak (in the short-run), one may argue that the banks' exposure to losses from the securities portfolio was marginal and thus the adjustment procedure will not materially affect estimation results.

other features,[12] the following empirical analysis employs a system of control variables for the inter-group differences.

=== Insert Table 1 here ===

The descriptive statistics allow some preliminary inferences about the determinants of portfolio structures. First we observe that, as expected, demand shares (*LAMBDA*) are positively associated with portfolio shares across all the seven sectors. Second, considering the levels of the relative (inter-sectoral) differences in the variability and correlation of credit cost (*VAR* and *RHO*), we see that the inter-sectoral diversification is likely to have a significant effect on the portfolio variance. In particular, three sectors (Construction, Real Estate, and Others) have noticeably large values of *VAR* and other two (Manufacturing and Services) large values of *RHO*. Third, the data in Table 1 also shows that lending to the seven sectors differs in the average size of stand-alone loan exposures: The unit size of loans to Others and Real Estate sectors is relatively large and that of loans to Construction and Trade is effectively small by comparison. But the coefficient of variation of *GAMMA* is similar for all the sectors (but Real Estate), thus suggesting that the cross-sectional variability of the indicator is driven more by differences in the size of the banks' portfolios than by differences in their regional exposures. Finally, it is worth noting that although the variability of our data for *VAR* and *RHO* is driven mostly by the banks' exposure to different regions, we still cannot make direct inferences about the benefits of geographic diversification. At most, we can conclude that since the correlation between the *VAR* (and *RHO*) series and the *DIST* series significantly varies in sign across the seven sectors,[13] the relative importance of the sectors in terms of inter-sectoral diversification changes as a bank increases its geographic reach.

For 381 banks, our data set contains observations for both business years, 2002 and 2003, and the feature raises the question about the degree of data variability over time. Table 2 reports changes in the data by year. We see that the level of variation in portfolio shares is apparently much smaller over time than across banks. It is no surprise because, by the nature of bank lending, bank loan portfolios do not typically

[12] For instance, our data on branch-office distribution (not reported) shows that, as a group, credit associations are also more rooted in rural markets and, arguably, face less competition.
[13] *VAR* exhibits positive correlation with *DIST* for Construction and negative (or zero) correlation for other sectors; *RHO* – positive correlation for Transport-Communications and Services and negative correlation for Manufacturing, Construction, and Other. The full set of correlations among the data is available upon request.

exhibit radical changes in their sectoral structure from year to year. Although the average maturity of SME lending barely exceeds one year, banks naturally tend to novate loans to existing clients already exhibiting a reliably sound borrowing history. Furthermore, the accumulation of monitoring expertise in a new field is a long-term process.

Table 2 also suggests a tendency towards geographic consolidation (*DIST*), small improvements in the banks' solvency levels (*DtD*), and some shifts in the relative (inter-sectoral) correlations of the credit cost (*RHO*), but it reports no significant change in the relative variability of the credit cost (*VAR*). Furthermore, the statistical association between the changes in *LAMBDA* and other variables is weak and does not exhibit clear pattern in signs.

=== Insert Table 2 here ===

The reduced variability of the data over time suggests concentrating our attention on the cross-sectional dimension and lends itself to the pooled-sample empirical setup. Specifically, we treat all observations as independent draws from the same population and account only for the aggregate effect of time on the dependent variable. The following empirical model is estimated:

$$\begin{aligned}\ln[LAMBDA_i] = a_0 + a_1 YEAR + a_2 \ln[ALFA_i] + a_3 \ln[DIST] + a_4 \ln[DtD] \\ + a_5 \ln[VAR_i] + a_6 \ln[RHO_i] + a_7 \ln[VAR_i]\ln[RHO_i] \\ + a_8 \ln[GAMMA_i] + a_9 \ln[VAR_i]\ln[GAMMA_i] + a_{10} \ln[RHO_i]\ln[GAMMA_i]\end{aligned} ,$$

where *YEAR* is a dummy variable for 2003 observations. To account for group-related heterogeneity we also introduce a system of dummy variables for the observations of commercial banks and credit cooperatives.

Table 3 summarizes some expected signs given the predictions of the previous section. Specifically, we expect a positive association between the observed portfolio weights (*LAMBDA*) and corresponding demand shares (*ALFA*) in all cases but switching signs for other variables. *VAR*, *RHO*, and *GAMMA* are expected to exhibit a negative association for banks with significantly high solvency (high levels of *DtD*) and to switch to a positive association when in a state of low solvency. The sign of *DIST* is uncertain but should also switch when the bank solvency is low. The signs of *YEAR* and the cross products are uncertain.

=== Insert Table 3 here ===

The empirical model is estimated using the seemingly unrelated regressions (SUR) approach. The choice is motivated by efficiency considerations because, although we use identical linear specifications for all the seven sectors, the model is still prone to cross-equation correlation in errors due to the possibility of commonly omitted variables. As suggested above, one should also exercise caution over whether the model is highly non-linear in the levels of *DtD* and whether the information lost in pooling by-year observations is material for one's inferences. To address the two points of concern, we test the consistency and significance of parameter change when the sample is split in two by *DtD* levels, and estimate the same model based on the by-year differences.[14]

IV. Estimation Results and Discussion

Table 4 reports SUR estimates of the model's parameters. The reported numbers for commercial banks and credit cooperatives are recalculated from the originally estimated cross products of the regressors and group dummies. The parameters were tested for the significance of differences between Manufacturing and other sectors.

=== Insert Table 4 here ===

The estimation results, first, indicate a strong and stable statistical association between the portfolio weights and structure of local demand in the case of credit associations. The expected sign is supported for all the sectors albeit with reduced significance for Construction and Trade. The result is quite appealing intuitively because when a banking organization fully exploits lending opportunities in its market segment the key economic sectors of the local economy become strongly presented in the structure of the bank's lending portfolio. By the same token, the strong statistical relationship suggests that credit associations are not very selective in terms of economic sectors their borrowers belong to. In the case of commercial banks and

[14] In addition, one may also be concerned about possible simultaneity in the data. In particular, one may suggest that the sectoral structure of local economies, which is effectively used as a proxy for the local loan demand, is dependent on the bank's willingness to lend to particular sectors, and therefore the levels of *LAMBDA* influence the levels of *ALFA* and, perhaps, of *VAR*. While admitting this possibility, we do not account for it in the estimation approach, because in our sample, for both *ALFA* and *VAR* we employ data which reflect the levels of economic activity at least one year before the time of *LAMBDA* measurements.

credit cooperatives, however, the parameter estimates for *ALFA* are mostly insignificant statistically (for banks) and unstable (for cooperatives). There are two competing explanations for the result. On the one hand, one can argue that these banks are strongly selective among loan applications in terms of their sectoral affiliation. On the other hand, the result can also be attributed to the nature of the loan demand proxy and interpreted as the structure of lending opportunities (these banks face) being significantly different from the sectoral structure of local economies. The choice between these two explanations should obviously rely on whether or not the portfolio structure of commercial banks and credit cooperatives is strongly driven by other suggested determinants of portfolio choice.

Unlike *ALFA* estimates, the effects of the variance-related variables (*VAR*, *RHO*, and *GAMMA*) are unstable and weak for all the groups of banks. For the credit associations, the effect of the relative credit cost variability *VAR* exhibits alternating signs and is significant only in one sector (Real Estate). The effect of the relative correlation of credit cost *RHO* shows 5% significance for three sectors (Manufacturing, Real Estate, Other), but is not consistent with the sign of *VAR*. Although one may argue that the observed signs may be switching across sectors because less solvent banks focus their lending on specific sectors,[15] the argument is not applicable within the same sector, because the signs of *VAR* and *RHO* for a sector should coincide when the portfolio choice is strongly driven by the variance considerations. Hence, we conclude that their estimates for Real Estate, for instance, are mutually inconsistent from the viewpoint of portfolio diversification. The same is true if compare with *GAMMA* estimates: They are again significant only for Real Estate but yet return conflicting signs.[16] In total, the results cast doubt on whether small Japanese banks strongly consider portfolio effects when deciding the sectoral structure of their loan portfolios. This is especially apparent in the case of lending to Construction and Services: Although the two sectors exhibit the largest potential in terms of variance effects (in the levels of *VAR* and *RHO* correspondingly), model estimation delivers no evidence of significant statistical association with *LAMBDA*.

In the case of commercial banks, the estimated variance effects are significant only for Manufacturing, yet the signs tend to alternate both across and within sectors.

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[15] Table 1 partially supports the view in the commercial bank case, but reports low levels of (average) correlation between *LAMBDA* and *DtD* for credit associations (12.5%) and cooperatives (9.3%).

[16] This sign inconsistency suggests the presence of other factors of portfolio decisions specific to this sector. In particular one may hypothesize that this is an outcome of the popular view of the real estate lending as one of the primary causes of the recent banking crisis.

The estimates for credit cooperatives are more significant statistically but show the same disagreement in signs: Whereas the signs of VAR and RHO agree for Manufacturing, Construction, and Real Estate, they disagree for other sectors. Furthermore, there is considerable sign variability across sectors: In most cases here the Wald test suggests that one cannot deny differences between the estimated parameters for Manufacturing versus other sectors at 1% and 5% significance levels.

These strong differences across sectors require one to explicitly test whether they are due to the effect of the banks' varying solvency on their portfolio policy, or they should be attributed to other factors. To test the effect statistically, we split the pooled sample into two sets with low and high levels of the *DtD* series.[17] As suggested by the model, a decline in a bank's solvency will first result in the reduced importance of the variance-related factors for its portfolio policy and then in their reemergence with an opposite sign. Given this relationship, the differences between the parameters estimated over the high-*DtD* set and the parameters estimated over the low-*DtD* set are expected to have the same signs as those in Table 3 for the variance-minimization case. Observing these signs will constitute evidence of a strong impact of the banks' varying solvency on their portfolio policy. Table 5 reports the signs of the parameter differences and the significance of the Wald test statistic for the differences. Although *VAR*, *RHO*, and *GAMMA* are all expected to have negative differences, the estimated differences have varying signs and, furthermore, none of the cases with a negative parameter difference is considered statistically significant. Hence, the test does not show any supportive evidence indicating a strong influence on the banks' portfolio policies by the differences in the solvency of the institutions. The cross-sectoral sign variability of the estimates in Table 4, therefore, should be attributed to other, unaccounted factors, and therefore, we can also conclude that the estimation results do not suggest any supportive evidence of the bank lending policy being strongly driven by portfolio considerations, even in the credit cooperative case.

=== Insert Table 5 here ===

Returning to Table 4 we see that the estimates for *DIST* reveal no significant relationship with *LAMBDA*. As noted above, however, *DIST* is used in our estimation to control for differences in the geographic reach of banks, and it does not readily lend

[17] The split point was suggested by the Chow test of structural change in parameters for the credit cooperative observations. Increasing the split point to the median of the entire sample has no material effect on the Wald test results for the credit association observations.

itself to making inferences about diversification effects.[18]

Similarly, the dummy variable for FY2003 observations (*YEAR*) is intended solely to control for the aggregate effect of by-year changes in the pooled sample. To confirm that pooling observations does not mask significant relationships, we estimated the same empirical model using by-year differences of the original data. Table 6 reports results of the additional round of estimation. As expected, the regression fit worsens, and parameter estimates lose significance in most sectors. We can see that the sign of *ALFA* estimates becomes unstable across sectors for all the groups of banks, while the variance-related effects (*VAR*, *RHO*, and *GAMMA*) behave in a sporadic way. In sum, the estimation results suggest two conclusions: (1) a one-year period is considerably too short for studying portfolio selection policies of banks and (2) the use of the pooled sample approach in this study does not lead to a significant loss of information.

=== Insert Table 6 here ===

V. Concluding Remarks

In this study we have empirically investigated the problem of whether or not banking organizations actively adjust the structure of their loan portfolios in order to alter the variance of portfolio returns. Unlike the previous research, we focus directly on the determinants of the portfolio structure because this empirical approach helps discern the degree to which banks purposely use the diversification effect. Yet, this approach allows for better detangling of the portfolio effects of diversification from its other (synergy and market-power) effects, enabling one to avoid using the questionable assumption that reduced credit concentration which necessarily leads to reduced variability of portfolio returns. The study relies on a unique large dataset encompassing Japanese data about both the structure of banks' loan portfolios categorized by industry and the various characteristics of the lending opportunities, in terms of their relative size and return variability.

The investigation has not found any evidence whatsoever indicating that small banks seriously take into account, or attach significant weight, to the effects of loan diversification across industries when deciding the structure of their loan portfolios.

[18] Furthermore, an additional (not reported) round of estimation using observations with high (above-the-median) *DIST* levels delivered no material differences in results compared to those of the main round of estimation. The additional estimates are available upon request.

The result is robust with respect to differences in the banks' solvency and their statutes. By comparison, we find a strong effect on the loan portfolio structures of small banks from the structure of the local loan demand. When taken together, these two findings suggest that the banks face reduced net benefits of adjusting their portfolio structures away from the structure of incoming loan applications. Although the data indicates that adjusting portfolio structures can lead to significant absolute changes in the variability of portfolio returns, we generally observe that the banks tend to discount the benefits of such adjustment in comparison to its costs.

The empirical results of this study support the view that the costs of diversification for banks prevail over its benefits – at least in the case of diversification across industries. The nature of the costs, however, is not clear: The results can be equally attributed to the presence of large direct costs of diversification and to the presence of better opportunities of adjusting loan interest rates. The question requires further investigation because this ambiguity prevents one from using the results both to decide between the "financial institution view" vs. "corporate finance view" and to formulate implications for the financial sector policy.

Geographic diversification is another important area of extension of the present study. Our estimates indicate 40% to 120% differences in the variance of credit cost across Japan's six major regions. Obtaining reliable data on inter-regional correlations will enable one to make a straightforward extension of the analysis to the issue of geographic diversification, which will help to highlight its differences vis-à-vis inter-industry diversification and, thereby reveal insight into complex forces driving the current wave of mergers among the nation's small banks.

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Appendix I. Utility effects of portfolio variance under limited liability

Direct differentiation gives:

$$\text{[A1]}\quad \frac{\partial U}{\partial \sigma_Q} = h[X] + \frac{\left(kQ_0 + E_{r_Q}\right)h'[X]}{\sigma_Q} - \frac{1}{2}Ag\left(2\sigma_Q - \frac{\sigma_Q\left(3\left(kQ_0 + E_{r_Q}\right)h[X]\sigma_Q + 2h[X]^2\sigma_Q{}^2 + \left(kQ_0 + E_{r_Q}\right)^2 h[X]^2\right)}{\left(kQ_0 + E_{r_Q} + h[X]\sigma_Q\right)^2}\right)$$

where $h'[X]=\partial h[X]/\partial X$. Since $h[X]>0$ by definition, it follows that

$$\text{[A2]}\quad h'[X] = h[X]^2 - h[X]X > 0 \quad \text{for all } X \leq 0.$$

By the nature of our problem, however, the bank must be viable at the start, that is, the expected value of its portfolio cannot be smaller than the money promised to depositors (i.e., $Q_1 \geq D$). Hence, $h'[X]$ is positive in our case. Now rearranging terms in the expression above we have:

$$\text{[A3]}\quad \frac{\partial U}{\partial \sigma_Q} = \left[\begin{array}{l} h[X] + \dfrac{\left(kQ_0 + E_{r_Q}\right)h'[X]}{\sigma_Q} \\ + Ag\dfrac{\sigma_Q\left(3\left(kQ_0 + E_{r_Q}\right)h[X]\sigma_Q + 2h[X]^2\sigma_Q{}^2 + \left(kQ_0 + E_{r_Q}\right)^2 h[X]^2\right)}{2\left(kQ_0 + E_{r_Q} + h[X]\sigma_Q\right)^2} \end{array}\right] - [Ag\sigma]$$

Both expressions in brackets are positive, and

$$\text{[A4]}\quad \lim_{\left(kQ_0 + E_{r_Q}\right)\to 0}\left[\frac{\partial U}{\partial \sigma_Q}\right] = \left[h[0] + 0 + Ag\frac{\sigma_Q\left(0 + 2h[X]^2\sigma_Q{}^2 + 0\right)}{2\left(0 + h[X]\sigma_Q\right)^2}\right] - \left[Ag\sigma_Q\right]$$
$$= \left[\sqrt{2/\pi} + Ag\sigma_Q\right] - \left[Ag\sigma_Q\right] > 0$$

If (kQ_0+E_{rQ}) is sufficiently larger than σ_Q, both $h'[\cdot]$ and $h[\cdot]$ approach 0, so that:

$$\text{[A5]}\quad \lim_{\left(\frac{\left(kQ_0 + E_{rQ}\right)}{\sigma_Q}\right)\to\infty}\left[\frac{\partial U}{\partial \sigma_Q}\right] = \left[0 + 0 + Ag\frac{\sigma_Q(0 + 0 + 0)}{2(1 + 0)^2}\right] - \left[Ag\sigma_Q\right] = [0] - \left[Ag\sigma_Q\right] < 0$$

Hence, $\partial U/\partial \sigma_Q$ turns from negative to positive values as (kQ_0+E_{rQ}) declines from large values to 0, and the position of the "turning point" depends on A and σ_Q.

Appendix II. Data construction

1. Loan demand structure

The structure of qualifying application inflow faced by individual banks is not observable. To assess a_i, we assume that the structure is determined by the characteristics of small business activity in each geographic region. In particular, we start with 2001 Enterprise Census data on labor force structure within each of Japan's 3200 strong municipalities and apply prefecture (city) specific weights of small business participation in each economic sector's employment in order to arrive at an estimate of the number of SME workers by municipality-sector. Then, assuming that in each region all firms belonging to a sector exhibit the same (prefecture-specific) labor productivity, we use the SME employment numbers to translate 2001 prefecture-level (per-worker) output of each sector to a municipality-level estimate of SME economic activity attributable to that economic sector. Finally, we apply prefecture-specific borrowings-to-asset (leverage) ratios to make the estimate suitable as a proxy of the local loan demand. The leverage ratios are calculated as (asset size weighted) averages of 2001 firm-level ratios derived from the CRD data file.

In sum, the procedure to estimate a proxy of SME loan demand generated by the i-th sector in the k-th municipality follows this algorithm:

$$\alpha_{k,i} = \{total\ employment\}_{k,i} \frac{\{SME\ employment\}_{c,i}}{\{total\ employment\}_{c,i}} \frac{\{output\}_{p,i}}{\{total\ employment\}_{p,i}} \{leverage\}_{p,i},$$

where i denotes the i-th economic sector (i = 1, 2, … 7) and k – the k-th low-level municipality (k = 1, 2, … 3296); c stands for the c-th intermediate-level municipal entity (c = 1, 2, … 199) and p for the p-th prefecture (r = 1, 2, … 47) the k-th municipality belongs to.

In the case of bank lending to individuals, we assume that the demand for such loans depends on the numbers of labor-force-participating people living in a municipality. The assumption allows us to leverage the statistics of the 2000 Population Census to break the nation-wide amount of bank lending to individuals down by municipality. As the last step we calibrate the estimate to that of the SME loan demand proxy by the ratio of 2001 GDP to nation-wide SME lending. The resulting proxy of individual lending demand (a_h) coming from the k-the municipality is:

$$\alpha_{kh} = \frac{\{working\ \ population\}_k}{\sum_k \left[\{working\ \ population\}_k\right]} \{lending\ to\ individuals\} \frac{\sum_p \sum_i \left[\{output\}_{p,i}\right]}{\{lending\ to\ SME\}}.$$

At the second step, the municipality-level proxy of sector-specific loan demand is translated into bank-level estimates. The mapping is based on the distribution of male bank employees across municipalities. The approach accounts for the fact that the loan officers of Japanese banks are predominantly male, whereas female employees are mostly responsible for teller operations and back-office clerical work. Hence, the number of male employees allocated to a municipality is roughly proportional to the inflow of loan applications generated by the municipality. In particular, we use the following mapping algorithm:

$$\alpha_{n,j,i} = \sum_k \left[\alpha_{k,i} \frac{\{bank\ male\ employees\}_{n,k,j}}{\{total\ bank\ male\ employees\}_{n,j}} \right],$$

where j denotes the j-th banking organization (j = 1, 2, … 851) and n – the n-th year (2002, 2003).

2. Credit cost variability

Finding a suitable proxy for return variability poses a major challenge to studying diversification effects. In this paper we exploit the opportunity offered by the CRD data file and attempt at direct estimation of credit cost variances-covariances as the primary source of variability in loan portfolio returns. In particular, we proceed in two steps. We first estimate the variability of credit cost across economic sectors for stand-alone exposures, and then adjust these estimates to account for sector-specific portfolio correlations.

Stand-alone variability estimation

Our measure of the stand-alone credit cost variability relies on the estimates of 1-year probability of default supplied in the CRD data file. The estimates are produced by the CRD Council's proprietary model which itself draws on the firm-level accounting information in the data file. The estimates are useful in two ways. First, if the default process is viewed as a Bernoulli binominal random variable, the estimates immediately give variance measures, because Var[X] = $p(1-p)$, if X ~ Bernoulli[p]. Second, the estimates can be used as a starting point in joint probability calculations. Since the distribution of averages of Bernoulli binominals approaches the Gaussian distribution, averages of the CRD default probability estimates can be viewed reflecting the cumulative probability of a normal variable falling below some threshold level. Hence, numerical approximation of the implied thresholds will give inputs to the bivariate normal formula, which in turn will lead to estimates of joint default

probabilities (if supplied with a suitable proxy for default process correlation).

In particular, we proceed as follows. Sound loans recorded in the CRD data file are divided into 1344 smaller samples by year (1995~2002), region (1~6), and industry (1~28). From each sample we calculate the average default probability weighted by the loan size and translate them into default variance and default threshold estimates. Following the modeling approach of Merton (1974), the default process is viewed as a firm's asset value declining below a default threshold, and, thus, one needs data on the asset value correlation of two firms to calculate the joint default probability of the firms. In our case, asset correlations are proxied by the correlation of annual changes in the market capitalization of stocks listed on the Tokyo Stock Exchange. The estimated correlation coefficients are then combined with the default variances and thresholds to numerically approximate joint cumulative probabilities of default over one year. The difference between the joint default probabilities and the products of default rates gives default covariance estimates.

The default rate estimates are an imprecise measure of credit cost and need to be adjusted by the level of losses incurred in default events. To assess the loss-given-default (LGD) rates, we assume that interest rates charged on new loans to sound borrowers are free from evergreening effects and reflect the banks' true expectation of both default and LGD rates. Following the logic we select CRD borrower records in the year of their first appearance in the data file and calculate the borrowing cost they pay in this year. Then we reduce the numbers by the expected funding cost, overhead cost and required owners' return and divide the result by the default rates experienced in the previous year. This gives implied levels of the LGD rate for each industry (1~28) over 1996-2002. Considering that the nation went through economic turbulence in these years, we finally take averages over 1996-2002 and use these industry-specific LGD rates to translate the default variability numbers to the estimates of credit cost variability.

In sum, the covariance ($\sigma_{v,w,n,r}$) of credit cost between loans to the v-th and w-th industries (v, w belong to m = 1, 2, … 28) in the n-th year and r-th region is calculated as follows:

$$DR_{m,n-1} = \frac{\sum_r \left[\{default\ rate\}_{m,n-1,r} \{loans\ in\ CRD\}_{m,n-1,r} \right]}{\sum_r \left[\{loans\ in\ CRD\}_{m,n-1,r} \right]}$$

$$LGD_{m,n} = \left\{ \begin{array}{l} \dfrac{\{borrowing\ cost\ of\ new\ sound\ CRD\ borrowers\}_{m,n}}{\{loans\ to\ new\ sound\ CRD\ borrowers\}_{m,n}} \\ -\{term\ deposit\ rate\}_n \\ -\dfrac{\sum_n \sum_j \left[\{overhead\ cost\}_{n,j}\right]}{\sum_n \sum_j \left[\{total\ assets\}_{n,j}\right]} - \dfrac{\sum_n \sum_j \left[\{net\ return\}_{n,j}\right]}{\sum_n \sum_j \left[\{total\ assets\}_{n,j}\right]} \end{array} \right\} \Big/ DR_{m,n-1}$$

$$LGD_m = \frac{1}{n} \sum_n \left[LGD_{m,n} \right]$$

$$\sigma_{v,w,n,r} = \{default\ rate\ covariance\}_{v,w,n,r}\, LGD_v LGD_w$$

Finally, the credit cost variance-covariance estimates for 28 industries are merged into estimates for 7 economic sectors to make the data directly comparable to the available information on the structure of banks' loan portfolios.

Adjustment for intra-sector portfolio correlations

The credit cost variability estimates obtained so far are based on the averaged default probabilities of stand-alone exposures and thus require a downward correction before they can be used as a proxy of return variability of sectoral sub-portfolios. For each sector, such adjustment should reflect both the prevailing size of stand-alone exposures within the sector and credit cost correlation between them. Unlike the average loan size, however, credit cost correlation is not directly observable and thus should be estimated. One possibility here is to model the correlations directly along the lines of the previous section. To do it, however, one would need an initial input of data on asset correlations, but available intra-industry estimates for stock returns are subject to much stronger noise than in the case of their inter-industry correlations. To circumvent the problem, we approach the estimation task through artificial data generation.

In particular, after removing CRD records with dubious levels of borrowing cost (those with the borrowing cost below 0.5% and above 18%) and past defaults, we arrange the entire file into 336 samples by having the records broken down by economic sector, region, and year. Then, over each sample we randomly choose a number of records so that their combined principal amount would (on average) be 0.1, 0.5, 1.0, 5.0, and 10.0 yen billion. For each of the five "virtual" portfolios we record their size and the share of loans declared in default in this year. This bootstrapping

procedure is repeated 1000 times to generate a sufficient sample of default rate observations for each of the virtual portfolios. Finally the generated observations are used to calculate default rate variance.

Figure 1 reports the average change in the estimated default rate variability by portfolio size. Loan portfolios in manufacturing, construction, transport-communication and wholesale-retail trade exhibit a similar declining tendency, which is well approximated as a power function of the portfolio size. Loans to other sectors also show some variance decline but with significantly different parameters and instability for small portfolios.

=== Insert Figure 1 here ===

The curvature parameter of the power function reflects the strength of intra-sectoral (default) correlation and readily lends itself as an adjustment factor. Specifically, the generated data relates the default variability (standard deviation, σ_{di}) of an imperfectly diversified sectoral portfolio to that of a perfectly diversified portfolio (σ_{di}-bar) through the number of stand-alone exposures (N_i) as:

$$\sigma_{di} = \overline{\sigma}_{di}\theta_0\left(\frac{1}{N_i}\right)^{\theta}$$

By the Taylor expansion around 1 we have:

$$\sigma_{di} \approx \overline{\sigma}_{di}\theta_0(1-\theta) + \overline{\sigma}_{di}\theta_0\frac{\theta}{N_i}$$

Now, noting that $\theta_0\sigma_{di}$-bar corresponds to the default variability of a single loan (N_i =1) and $(1-\theta)\theta_0\sigma_{di}$-bar – to that of the perfectly diversified portfolio ($N_i = \infty$), we see that $(1-\theta)$ is close the adjustment factor we need.

In particular we proceed as follows. For each "sector×region" combination we fit the power function curve to 40 variance measurements and calculate its curvature parameter (θ_{ri}). The parameter reflects the region-specific level of intra-sectoral correlation averaged over 1995-2002. Then, for the covariance estimate ($\sigma_{x,y,n,r}$) between the x-th and y-th sectors (x, y belong to i = 1, 2, … 7) the adjustment becomes:

$$\overline{\sigma_{x,y,n,r}} = \sigma_{x,y,n,r}(1-\theta_{x,r})(1-\theta_{y,r})$$

At the final step, the estimates are mapped onto the regional distribution of banks' labor force (at year n) to arrive at bank-level numbers as follows:

$$\sigma_{x,y,n,j} = \sum_r \left[\overline{\sigma_{x,y,n,r}} \frac{\{bank\ male\ employees\}_{n,r,j}}{\{total\ bank\ male\ employees\}_{n,j}} \right],$$

where r denotes the r-th region (r = 1, 2, … 6).

3. Other data

Geographic diversification

In order to control for the variance effects of geographic diversification, we employ a measure of geographic dispersion of a bank's branch network. The measure was constructed as a weighted average distance among the male employees of the bank. Specifically, we calculate Euclidian distances among the town halls of the nation's low-level municipalities and attach weights according to the share of male employees allocated to each municipality. The procedure for the j-th bank in the n-th year looks as follows:

$$g_{n,j} = \sum_k \sum_k \left[\{dis\tan ce\}_{a,b} \frac{\{bank\ male\ employees\}_{n,a,j}}{\{total\ bank\ male\ employees\}_{n,j}} \frac{\{bank\ male\ employees\}_{n,b,j}}{\{total\ bank\ male\ employees\}_{n,j}} \right]$$

where a and b denote the a-th and b-th municipalities (a, b belong to k = 1, 2, … 3296).

Distance to default

The modeling exercise of Section II shows that the banks' portfolio policy may be strongly influenced by the probability of their failure. As argued above, it can be proxied by the ratio of a bank's expected wealth to the return variability of its assets. For simplicity sake we assume here that the expected wealth equals the bank's mid-year capital-to-asset ratio, and its asset return variability is well reflected by that of the loan portfolio. To avoid endogeneity concerns, the standard deviation of portfolio return is calculated using not the observed weights, but their estimates for the structure of loan demand:

$$\sigma_{n,j} = \sqrt{\sum_i \sum_i \left[\sigma_{x,y,n,j} \alpha_{n,j,x} \alpha_{n,j,y} \right]}$$

$$\{dis\tan ce\ to\ default\}_{n,j} =$$

$$= \left(\frac{\{own\ funds\}_{j,n-midyear}}{\{total\ assets\}_{j,nn-midyear}} \right) \Bigg/ \left(\sigma_{n,j} \frac{\{total\ assets\}_{j,n-midyear} - \{non-loan\ assets\}_{j,n-midyear}}{\{total\ assets\}_{j,n-midyear}} \right)$$

Relative portfolio size

In order to control for the variance effects of (the inverse of) portfolio size, we use mid-year estimates of balance-sheet values of banks' loan portfolios and the sector-specific average sizes of loan exposures calculated in the course of the bootstrap experiment from the CRD data file. The average size numbers are translated to by-bank estimates ($\gamma_{n,i,j}$) using the following mapping procedure:

$$\gamma_{n,i,j} = \sum_{r} \left[\{average\ loan\ size\}_{i,r} \frac{\{bank\ male\ employees\}_{n,r,j}}{\{total\ bank\ male\ employees\}_{n,j}} \right]$$

Table 1. Descriptive statistics of the pooled sample (FY 2002, 2003)

		Credit Associations				Credit Cooperatives				Commercial Banks			
No. of observations		550				208				93			
		Mean	Median	Std. Dev	Correlation v. *LAMBDA*	Mean	Median	Std. Dev	Correlation v. *LAMBDA*	Mean	Median	Std. Dev	Correlation v. *LAMBDA*
Portfolio Size		189703	96609	266220		54633	36988	60435		780462	574695	562642	
DIST		14.7	10.4	15.1		16.5	10.4	26.2		53.7	49.4	24.5	
DtD		2.25	2.06	1.09		1.94	1.48	1.53		1.18	1.20	0.32	
Manufacturing	*LAMBDA*	0.118	0.104	0.067		0.096	0.075	0.081		0.099	0.098	0.038	
	ALFA	0.058	0.053	0.025	0.171	0.058	0.056	0.024	0.284	0.047	0.044	0.011	-0.122
	VAR	-0.00121	-0.00124	0.00108	-0.008	-0.00113	-0.00124	0.00106	0.174	-0.00099	-0.00045	0.00099	-0.085
	RHO	0.174	0.169	0.013	0.260	0.173	0.169	0.013	0.150	0.175	0.169	0.012	0.556
	GAMMA	-0.00119	-0.00022	0.00290	-0.005	-0.00364	-0.00105	0.01321	0.121	-0.00012	-0.00005	0.00017	0.154
	Portf. Size				0.221				0.119				0.151
	DIST				-0.146				-0.036				0.009
	DtD				0.070				-0.035				0.118
Construction	*LAMBDA*	0.116	0.113	0.036		0.113	0.113	0.055		0.093	0.093	0.021	
	ALFA	0.146	0.134	0.068	0.047	0.131	0.121	0.064	0.072	0.132	0.126	0.056	-0.010
	VAR	0.00432	0.00169	0.00539	0.101	0.00414	0.00169	0.00527	0.279	0.00351	0.00155	0.00455	0.101
	RHO	-0.050	-0.046	0.027	0.146	-0.052	-0.049	0.027	-0.155	-0.050	-0.044	0.024	0.075
	GAMMA	-0.00145	-0.00058	0.00297	-0.042	-0.00467	-0.00160	0.01373	0.000	-0.00015	-0.00006	0.00017	-0.181
	Portf. Size				-0.226				0.056				-0.452
	DIST				0.105				0.133				0.071
	DtD				0.063				-0.079				0.209
Transp-t-Comm.	*LAMBDA*	0.024	0.019	0.033		0.025	0.012	0.073		0.034	0.030	0.019	
	ALFA	0.101	0.093	0.037	0.216	0.105	0.092	0.048	0.236	0.104	0.102	0.023	0.166
	VAR	0.00118	0.00109	0.00210	0.067	0.00108	0.00109	0.00211	0.004	0.00139	0.00209	0.00185	0.279
	RHO	-0.033	-0.024	0.021	0.132	-0.032	-0.024	0.020	0.031	-0.031	-0.021	0.018	0.088
	GAMMA	-0.00109	-0.00015	0.00296	0.005	-0.00321	-0.00051	0.01342	0.033	-0.00010	-0.00003	0.00017	0.180
	Portf. Size				-0.027				-0.008				0.190
	DIST				0.006				0.082				0.249
	DtD				-0.062				-0.056				-0.146
Trade	*LAMBDA*	0.118	0.113	0.038		0.123	0.119	0.077		0.121	0.122	0.032	
	ALFA	0.044	0.041	0.013	0.036	0.045	0.041	0.019	0.005	0.045	0.043	0.008	-0.065
	VAR	0.00011	-0.00008	0.00085	0.003	0.00006	-0.00008	0.00079	0.072	0.00010	-0.00036	0.00083	-0.399
	RHO	-0.006	-0.005	0.022	-0.090	-0.002	-0.005	0.022	-0.104	-0.004	-0.005	0.024	-0.022
	GAMMA	-0.00127	-0.00047	0.00265	0.043	-0.00406	-0.00142	0.01222	-0.109	-0.00014	-0.00006	0.00015	0.250
	Portf. Size				-0.010				-0.034				0.273
	DIST				0.010				-0.087				0.400
	DtD				0.048				-0.021				0.299
Real Estate	*LAMBDA*	0.117	0.105	0.065		0.081	0.064	0.087		0.117	0.107	0.051	
	ALFA	0.056	0.053	0.020	0.409	0.052	0.046	0.024	0.427	0.069	0.071	0.012	0.297
	VAR	-0.00187	-0.00179	0.00138	-0.029	-0.00184	-0.00179	0.00134	0.069	-0.00173	-0.00101	0.00120	0.256
	RHO	0.008	0.015	0.013	-0.071	0.006	0.015	0.013	0.048	0.005	0.001	0.013	-0.163
	GAMMA	0.00032	0.00044	0.00261	0.040	0.00259	0.00194	0.01161	-0.039	0.00014	0.00009	0.00028	0.311
	Portf. Size				0.184				0.178				0.115
	DIST				0.009				-0.057				-0.369
	DtD				-0.181				-0.101				-0.191

Table 1. (continued)

		Credit Associations				Credit Cooperatives				Commercial Banks			
		Mean	Median	Std. Dev	Correlation v. *LAMBDA*	Mean	Median	Std. Dev	Correlation v. *LAMBDA*	Mean	Median	Std. Dev	Correlation v. *LAMBDA*
Services	*LAMBDA*	0.147	0.142	0.049		0.126	0.116	0.058		0.165	0.157	0.037	
	ALFA	0.181	0.176	0.036	0.235	0.189	0.188	0.036	0.006	0.188	0.184	0.026	0.092
	VAR	0.00027	0.00074	0.00152	-0.249	0.00036	0.00074	0.00151	-0.146	0.00040	0.00087	0.00132	-0.209
	RHO	-0.130	-0.133	0.039	0.085	-0.129	-0.133	0.040	0.040	-0.141	-0.158	0.040	-0.007
	GAMMA	-0.00128	-0.00035	0.00296	-0.175	-0.00394	-0.00118	0.01356	0.018	-0.00013	-0.00005	0.00017	-0.232
	Portf. Size				-0.110				0.157				-0.211
	DIST				0.193				-0.015				0.223
	DtD				-0.024				-0.170				-0.080
Other	*LAMBDA*	0.026	0.020	0.022		0.029	0.018	0.037		0.051	0.048	0.020	
	ALFA	0.152	0.151	0.046	0.314	0.158	0.155	0.053	-0.068	0.160	0.166	0.033	0.124
	VAR	-0.00280	-0.00303	0.00126	-0.211	-0.00268	-0.00303	0.00131	-0.031	-0.00268	-0.00261	0.00107	0.132
	RHO	0.045	0.031	0.035	-0.067	0.044	0.031	0.032	0.253	0.054	0.063	0.032	0.182
	GAMMA	0.00597	0.00065	0.01656	0.310	0.01692	0.00224	0.07512	-0.038	0.00050	0.00009	0.00094	-0.063
	Portf. Size				-0.241				-0.096				-0.199
	DIST				0.263				0.131				-0.191
	DtD				0.426				0.188				0.124

Notes: *LAMBDA* denotes the observed share of loans to the *i*-th sector in the credit portfolio of a bank at the end of a business year (March 2003 or March 2004); *ALFA* – a proxy of the loan demand by SMEs in the local lending market segment of a bank; *VAR* – the difference between the variances of credit cost of (1-year to maturity) loans to a sector and of in the rest of the portfolio on average in the previous three years; *RHO* – the difference between the average correlation of a sector's credit cost vis-à-vis other sectors and the average correlation among other sectors in the previous three years; *GAMMA* – the difference between the average size of a stand-alone loan exposure in a sector and that on average across the rest of the portfolio, divided by a mid-year estimate of the loan portfolio size of a bank ("Portfolio Size"); *DIST* – the weighted average physical distance between a bank's employees at the end of the previous year; *DtD* – the number of standard deviations of portfolio return covered by a bank's own funds (a mid-year estimate). For further details and data sources refer to Appendix II.

Table 2. Descriptive statistics of by-year differences (2003 data – 2002 data)

		Credit Associations				Credit Cooperatives				Commercial Banks			
No. of observations		246				93				42			
		Mean	Median	Std. Dev	Correlation v. *LAMBDA*	Mean	Median	Std. Dev	Correlation v. *LAMBDA*	Mean	Median	Std. Dev	Correlation v. *LAMBDA*
Portfolio Size		186333	92151	272035		47154	34072	44697		759665	561058	507388	
DIST		-0.05	0.00	0.53		-0.17	0.00	0.72		-0.12	-0.07	2.16	
DtD		0.13	0.12	0.17		0.13	0.10	0.30		0.06	0.06	0.09	
Manufacturing	*LAMBDA*	-0.004	-0.004	0.015		-0.003	-0.002	0.017		-0.003	-0.003	0.005	
	ALFA	0.000	0.000	0.001	0.157	0.000	0.000	0.001	-0.014	0.000	0.000	0.001	-0.021
	VAR	0.000000	0.000000	0.000001	0.004	0.000000	0.000000	0.000000	-0.014	-0.000002	0.000000	0.000007	-0.169
	RHO	-0.0002	-0.0013	0.0056	0.017	-0.0004	-0.0013	0.0057	0.004	-0.0001	0.0015	0.0047	-0.018
	GAMMA	-0.00016	-0.00013	0.03155	0.248	-0.00704	-0.00166	0.04272	0.030	-0.00018	-0.00003	0.00068	-0.364
	Portf. Size				-0.049				-0.187				0.045
	DIST				0.050				0.233				-0.065
	DtD				-0.169				0.434				-0.062
Construction	*LAMBDA*	-0.007	-0.006	0.014		-0.005	-0.002	0.016		-0.006	-0.006	0.005	
	ALFA	0.000	0.000	0.001	0.074	0.000	0.000	0.001	-0.073	0.000	0.000	0.001	0.307
	VAR	0.000000	0.000000	0.000004	-0.002	0.000000	0.000000	0.000000	-0.034	0.000007	0.000000	0.000035	0.015
	RHO	0.0081	0.0078	0.0088	-0.031	0.0082	0.0076	0.0085	0.040	0.0075	0.0076	0.0080	0.222
	GAMMA	-0.00041	-0.00043	0.03287	0.025	-0.00891	-0.00378	0.04553	-0.105	-0.00019	-0.00005	0.00074	-0.150
	Portf. Size				0.077				-0.240				0.112
	DIST				0.002				0.062				-0.065
	DtD				0.015				0.283				0.271
Transp-t-Comm.	*LAMBDA*	0.000	0.000	0.003		-0.005	0.000	0.030		0.001	0.000	0.005	
	ALFA	0.000	0.000	0.001	0.023	0.000	0.000	0.002	0.002	0.000	0.000	0.001	0.154
	VAR	0.000000	0.000000	0.000005	-0.009	0.000000	0.000000	0.000000	0.001	-0.000001	0.000000	0.000009	-0.137
	RHO	-0.0002	-0.0020	0.0132	0.111	0.0006	-0.0020	0.0137	0.046	0.0005	-0.0016	0.0112	-0.139
	GAMMA	-0.00012	-0.00010	0.03193	0.046	-0.00610	-0.00156	0.04296	-0.068	-0.00017	-0.00001	0.00069	-0.242
	Portf. Size				0.015				0.058				-0.042
	DIST				-0.032				0.324				0.005
	DtD				0.024				0.066				0.147
Trade	*LAMBDA*	-0.005	-0.004	0.008		-0.027	-0.017	0.039		-0.005	-0.002	0.010	
	ALFA	0.000	0.000	0.000	0.111	0.000	0.000	0.000	-0.170	0.000	0.000	0.000	-0.071
	VAR	0.000000	0.000000	0.000006	-0.061	0.000000	0.000000	0.000000	0.028	0.000000	0.000000	0.000006	0.197
	RHO	-0.0021	-0.0014	0.0042	0.036	-0.0023	-0.0014	0.0040	-0.026	-0.0024	-0.0014	0.0038	0.092
	GAMMA	-0.00034	-0.00033	0.02925	-0.078	-0.00765	-0.00352	0.04040	-0.074	-0.00017	-0.00005	0.00067	-0.246
	Portf. Size				0.012				-0.116				0.084
	DIST				-0.042				-0.009				0.081
	DtD				0.030				0.266				0.150
Real Estate	*LAMBDA*	0.008	0.005	0.015		0.002	0.001	0.018		0.004	0.002	0.011	
	ALFA	0.000	0.000	0.001	0.001	0.000	0.000	0.001	0.062	0.000	0.000	0.001	0.175
	VAR	0.000000	0.000000	0.000001	0.016	0.000000	0.000000	0.000000	0.008	-0.000001	0.000000	0.000007	0.149
	RHO	-0.0030	-0.0007	0.0056	0.055	-0.0032	-0.0007	0.0059	0.048	-0.0025	-0.0003	0.0052	-0.057
	GAMMA	0.00121	0.00042	0.02136	-0.051	0.00734	0.00244	0.04468	-0.111	-0.00010	0.00002	0.00095	0.248
	Portf. Size				0.006				0.013				-0.010
	DIST				-0.029				0.156				-0.004
	DtD				-0.014				-0.041				-0.033

Table 2. (continued)

		Credit Associations				Credit Cooperatives				Commercial Banks			
		Mean	Median	Std. Dev	Correlation v. *LAMBDA*	Mean	Median	Std. Dev	Correlation v. *LAMBDA*	Mean	Median	Std. Dev	Correlation v. *LAMBDA*
Services	*LAMBDA*	-0.001	-0.001	0.010		0.010	0.013	0.033		-0.002	-0.003	0.008	
	ALFA	0.000	0.000	0.001	0.064	0.000	0.000	0.001	0.005	0.000	0.000	0.001	0.086
	VAR	0.000000	0.000000	0.000002	-0.031	0.000000	0.000000	0.000000	-0.003	-0.000002	0.000000	0.000010	-0.015
	RHO	-0.0037	-0.0023	0.0027	0.024	-0.0033	-0.0023	0.0027	-0.123	-0.0035	-0.0032	0.0029	0.059
	GAMMA	-0.00023	-0.00016	0.03238	-0.207	-0.00709	-0.00202	0.04416	0.272	-0.00018	-0.00003	0.00073	-0.037
	Portf. Size				-0.125				-0.041				0.232
	DIST				0.047				-0.026				-0.112
	DtD				0.203				0.075				0.122
Other	*LAMBDA*	-0.001	-0.001	0.003		-0.002	-0.001	0.010		-0.001	-0.001	0.008	
	ALFA	0.000	0.000	0.002	-0.175	0.000	0.000	0.003	0.085	0.000	0.000	0.002	-0.027
	VAR	0.000000	0.000000	0.000001	0.022	0.000000	0.000000	0.000000	-0.016	-0.000002	0.000000	0.000009	-0.111
	RHO	0.0013	-0.0060	0.0123	0.013	0.0005	-0.0060	0.0124	0.110	0.0006	-0.0039	0.0108	0.253
	GAMMA	0.00005	0.00014	0.17841	0.105	0.02945	0.00144	0.23988	-0.002	0.00099	0.00005	0.00370	0.058
	Portf. Size				-0.001				-0.095				-0.360
	DIST				-0.016				0.265				-0.024
	DtD				-0.054				-0.048				0.014

Notes: for variable definitions and data sources refer to Table 1. "Portfolio Size" is given in 2004 levels (no by-year differencing).

Table 3. Expected signs in the empirical model

	Variance Minimization (high levels of *DtD*)	Variance Maximization (low levels of *DtD*)
ALFA	plus	plus
VAR	minus	plus
RHO	minus	plus
GAMMA	minus	plus

Table 4. Estimation results for the pooled sample (FY 2002, 2003)

Sector / Regressor	Manufacturing		Construction		Transport-Commun.		Trade		Real Estate		Services		Other	
	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.
Credit Associations (the base case)														
Constant	14490.8	-	747.3	-	778.7	-	-91.6	-	3944.7	-	3950.1	-	-833.9	-
	(1.70*)		(0.45)		(0.30)		(-0.30)		(3.49***)		(1.46)		(-0.46)	
YEAR	-0.097	-	-0.077		0.015		-0.037		0.120	**	0.015		0.087	*
	(-1.96**)		(-1.39)		(0.17)		(-0.62)		(1.70*)		(0.34)		(0.99)	
Ln(*ALFA*)	0.419	-	0.042	***	0.676	*	0.160	*	0.523		0.325		0.224	
	(6.75***)		(0.72)		(5.38***)		(1.19)		(5.25***)		(3.02***)		(1.87*)	
Ln(*DIST*)	-0.010	-	-0.003		0.031	*	0.010		-0.007		0.000		0.044	**
	(-0.86)		(-0.25)		(1.67*)		(0.73)		(-0.38)		(0.02)		(2.36**)	
Ln(*DtD*)	-0.048	-	-0.030		-0.097		0.013		-0.232	*	-0.005		0.468	***
	(-0.85)		(-0.49)		(-1.06)		(0.18)		(-2.83***)		(-0.10)		(4.93***)	
Ln(*VAR*)	-1423480	-	-51221		102625		237544		1019880	***	304460	*	-231494	
	(-1.61)		(-0.51)		(0.08)		(0.15)		(2.98***)		(0.68)		(-0.55)	
Ln(*RHO*)	-123651	-	3243	**	-5858		-9848	*	-212539		35788	***	-28047	*
	(-2.44**)		(0.17)		(-0.07)		(-0.22)		(-4.41***)		(1.68*)		(-2.02**)	
Ln(*VAR*) ×Ln(*RHO*)	-23036	-	-86	***	579	***	-3708	***	-14573		-411	***	14346	***
	(-9.21***)		(-0.18)		(0.45)		(-2.20**)		(-2.57***)		(-0.97)		(3.62***)	
Ln(*GAMMA*)	-6293.1	-	-325.4		-339.3		39.0	*	-1713.3		-1716.1		359.6	*
	(-1.70*)		(-0.45)		(-0.30)		(0.30)		(-3.49***)		(-1.46)		(0.46)	
Ln(*VAR*) ×Ln(*GAMMA*)	619771	-	22251		-44537		-103229		-442887	***	-132268	*	100315	
	(1.61)		(0.51)		(-0.08)		(-0.15)		(-2.98***)		(-0.68)		(0.55)	
Ln(*RHO*) ×Ln(*GAMMA*)	53698	-	-1407	**	2545		4277	*	92293		-15543	***	12201	*
	(2.44**)		(-0.17)		(0.07)		(0.22)		(4.41***)		(-1.68*)		(2.02**)	
Commercial Banks (derived)														
Constant	96776.8	-	-16479.1	-	-37938.1	-	-3625.5	-	-4984.3	-	65376.1	-	19563.7	-
	(2.26**)		(-0.38)		(-0.44)		(-0.29)		(-0.20)		(1.30)		(0.63)	
YEAR	0.007	-	-0.064		0.043		-0.049		0.022		-0.021		-0.033	
	(0.06)		(-0.47)		(0.21)		(-0.33)		(0.12)		(-0.19)		(-0.16)	
Ln(*ALFA*)	-0.597	-	0.034	*	0.141		0.021		0.827	**	0.057		0.004	
	(-1.80*)		(0.22)		(0.31)		(0.04)		(1.63)		(0.14)		(0.01)	
Ln(*DIST*)	0.274	-	0.139		0.039		0.257		-0.185		0.222		-0.111	
	(1.51)		(0.77)		(0.16)		(1.35)		(-0.84)		(1.38)		(-0.44)	
Ln(*DtD*)	0.161	-	0.257		-0.402		0.278		-0.499	*	0.056		0.300	
	(0.72)		(1.03)		(-1.05)		(0.89)		(-1.53)		(0.26)		(0.70)	
Ln(*VAR*)	27152600	-	-1313530	*	-24707500		26711200		-10490600	*	3647670		4523420	
	(1.65*)		(-0.46)		(-0.89)		(0.77)		(-0.67)		(0.39)		(0.63)	
Ln(*RHO*)	-123614	-	-792233		-577928		612194		-970320		353340		-209076	
	(-2.44**)		(-1.18)		(-0.20)		(0.51)		(-1.08)		(0.91)		(-0.84)	
Ln(*VAR*) ×Ln(*RHO*)	-3904	-	1042		84		3492		906		-132		4143	
	(-0.41)		(0.77)		(0.02)		(0.91)		(0.05)		(-0.10)		(0.36)	
Ln(*GAMMA*)	-42034.1	-	7155.6	*	16474.9		1573.2	**	2165.1	**	-28393.8		-8497.6	
	(-2.26**)		(0.38)		(0.44)		(0.29)		(0.20)		(-1.30)		(-0.63)	
Ln(*VAR*) ×Ln(*GAMMA*)	-11792100	-	570488	*	10730400		-11600600		4556040	*	-1584130		-1964490	
	(-1.65*)		(0.46)		(0.89)		(-0.77)		(0.67)		(-0.39)		(-0.63)	
Ln(*RHO*) ×Ln(*GAMMA*)	53698	-	344064		250992		-265875		421396		-153455		90806	
	(2.44**)		(1.18)		(0.20)		(-0.51)		(1.08)		(-0.91)		(0.84)	

Table 4. (continued)

Sector / Regressor	Manufacturing		Construction		Transport-Commun.		Trade		Real Estate		Services		Other	
	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.
Credit Cooperatives (derived)														
Constant	4806.8 (1.60)	-	-693.1 (-1.22)	-	53.3 (0.06)	-	183.6 (1.79*)	-	3106.6 (9.71***)	-	-519.1 (-0.57)	-	-1093.7 (-1.65*)	-
YEAR	0.022 (0.28)	-	-0.096 (-1.07)		0.237 (1.72*)		-0.445 (-4.62***)	***	0.058 (0.51)		0.160 (2.29**)		-0.075 (-0.54)	
Ln(*ALFA*)	0.902 (10.29***)	-	-0.191 (-2.08**)	***	-0.257 (-1.59)	***	-0.696 (-4.19***)	***	1.047 (8.04***)		0.283 (1.52)	***	-0.391 (-2.20**)	***
Ln(*DIST*)	0.050 (4.33***)	-	0.096 (7.28***)	***	0.097 (5.20***)	**	0.022 (1.62)		0.010 (0.55)	*	0.027 (2.68***)		0.011 (0.57)	*
Ln(*DtD*)	-0.023 (-0.29)	-	0.173 (2.11**)	*	-0.660 (-5.53***)	***	0.207 (2.26**)	*	-0.208 (-1.81*)		-0.029 (-0.43)		0.160 (1.30)	
Ln(*VAR*)	-725456 (-2.35**)	-	63671 (1.78*)	**	-481898 (-1.05)		1331820 (2.32**)	***	1219000 (14.17***)	***	-714094 (-4.58***)		-203621 (-1.33)	
Ln(*RHO*)	-47816 (-2.65***)	-	4654 (0.77)	***	48463 (1.55)	***	-20095 (-1.30)		79982 (5.31***)	***	13452 (1.92*)	***	24601 (4.99***)	***
Ln(*VAR*) ×Ln(*RHO*)	-7841 (-1.90*)	-	756 (1.06)	**	9187 (4.46***)	***	-7191 (-2.96***)		-13688 (-1.80*)		-2474 (-3.38***)		12043 (1.95*)	**
Ln(*GAMMA*)	-2087.0 (-1.60)	-	299.6 (1.22)	*	-25.3 (-0.06)		-81.7 (-1.83*)		-1348.8 (-9.71***)		224.9 (0.57)	*	471.9 (1.64)	*
Ln(*VAR*) ×Ln(*GAMMA*)	315685 (2.35**)	-	-27618 (-1.78*)	**	209413 (1.05)		-578408 (-2.32**)	***	-529296 (-14.18***)	***	310041 (4.58***)		88135 (1.33)	
Ln(*RHO*) ×Ln(*GAMMA*)	20763 (2.65***)	-	-2024 (-0.77)	***	-21050 (-1.55)	***	8732 (1.30)		-34738 (-5.31***)	***	-5840 (-1.92*)	***	-10667 (-4.98***)	***
R-squared	0.35		0.16		0.29		0.11		0.47		0.22		0.25	

Notes:

1. The table reports the model's parameters estimated by the SUR method over the pooled (FY2002 + FY2003) sample. The total number of observations is 851. *t*-statistics are in parentheses. ***, **, and * denote 1%, 5%, and 10% significance levels correspondingly.
2. Columns under "Wald t." heading indicate significance of the Wald test statistic for parameter differences (Manufacturing vs. other sectors).
3. The reported parameter estimates for commercial banks and credit cooperatives are derived from the original estimation results for the cross-products of the regressors and group dummies.
4. *YEAR* denotes a dummy for FY2003 observations. For other variable definitions and data sources refer to Table 1.

Table 5. Differences in the parameter estimates for the pooled sample split by *DtD* levels

Sector	Manufacturing		Construction		Transport-Commun.		Trade		Real Estate		Services		Other	
Regressor	Diff. Sign	Wald t.	Diff. Sign	Wald t.	Diff. Sign	Wald t.	Diff. Sign	Wald t.	Diff. Sign	Wald t.	Diff. Sign	Wald t.	Diff. Sign	Wald t.
Credit Associations + Commercial Banks (the base case)														
Constant	minus		minus		plus		plus		plus		plus	**	minus	**
YEAR	minus	*	plus		minus		plus		plus		plus		plus	
Ln(*ALFA*)	minus		minus		plus		plus		minus	*	plus	*	minus	**
Ln(*DIST*)	plus	*	plus		minus		plus		plus		plus		minus	***
Ln(*DtD*)	plus		minus		plus		minus		minus		minus		minus	
Ln(*VAR*)	minus		minus		plus		plus		plus	***	plus	*	minus	**
Ln(*RHO*)	plus		minus		minus		plus		plus		plus	*	plus	
Ln(*VAR*)×Ln(*RHO*)	minus		plus		minus		minus		minus		minus		plus	
Ln(*GAMMA*)	plus		plus		minus		minus		minus		minus	**	plus	**
Ln(*VAR*)×Ln(*GAMMA*)	plus		plus		minus		minus		minus	***	minus	*	plus	**
Ln(*RHO*)×Ln(*GAMMA*)	minus		plus		plus		minus		minus		minus	*	minus	
Credit Cooperatives (derived)														
Constant	minus		plus		plus		minus		minus	***	plus		plus	
YEAR	minus		minus		plus		plus		plus	*	minus		minus	
Ln(*ALFA*)	plus	**	plus		minus		minus		minus		plus	**	minus	*
Ln(*DIST*)	plus		plus	***	plus		minus		plus		minus		plus	
Ln(*DtD*)	plus		plus		minus	*	plus	***	minus	*	plus	*	plus	
Ln(*VAR*)	minus		plus		plus		plus		minus		plus		minus	
Ln(*RHO*)	plus		plus		plus		minus		plus	*	plus		minus	
Ln(*VAR*)×Ln(*RHO*)	minus		minus		plus	*	plus		minus	***	minus		plus	***
Ln(*GAMMA*)	plus		minus		minus		plus		plus	***	minus		minus	
Ln(*VAR*)×Ln(*GAMMA*)	plus		minus		minus		minus		plus		minus		plus	
Ln(*RHO*)×Ln(*GAMMA*)	minus		minus		minus		plus		minus	*	minus		plus	
R-squared	0.35		0.18		0.30		0.12		0.50		0.25		0.23	

Notes:

1. The table reports the signs of differences between parameters estimated over observations with high vs. low *DtD* levels. The pooled (2002+2003) sample was split into two sets at *DtD* = 1.34. The low-*DtD* set included 249 observations (102 of credit associations, 61 of commercial banks and 86 of credit cooperatives), and the high-*DtD* set – 602 observations (448, 32, and 122 of each group correspondingly). A dummy variable and its cross-products with the regressors were used to estimate parameters over each set. The differences were calculated as {High *DtD* estimates} minus {Low *DtD* estimates}.
2. Columns under "Wald t." heading indicate significance of the Wald test statistic for the parameter differences. ***, **, and * denote 1%, 5%, and 10% significance levels correspondingly.
3. For other notes refer to Table 4.

Table 6. Estimation results for by-year differences (2003 data – 2002 data)

Sector / Regressor	Manufacturing		Construction		Transport-Commun.		Trade		Real Estate		Services		Other	
	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.
Credit Associations (the base case)														
Constant	5.39	-	-29.01	-	1.12	-	5.57	-	1.02	-	-9.50	-	0.64	-
	(0.67)		(-2.47**)		(0.09)		(0.33)		(0.93)		(-0.37)		(0.59)	
Ln(*ALFA*)	1.02	-	1.46		-0.18		2.03		0.17		0.43		-0.36	
	(0.97)		(1.91*)		(-0.18)		(0.45)		(0.16)		(0.34)		(-1.95*)	
Ln(*DIST*)	0.013	-	0.004		0.000		-0.005		-0.008		0.007		-0.001	
	(0.87)		(0.24)		(0.02)		(-0.23)		(-0.49)		(0.35)		(-0.22)	
Ln(*DtD*)	-0.131	-	0.081	**	0.009	*	0.000		-0.027		0.113	**	-0.020	*
	(-2.21**)		(1.29)		(0.14)		(0.00)		(-0.44)		(1.42)		(-0.81)	
Ln(*VAR*)	146839000	-	26210300		-11607600		17374600		-13226100		-4608950		-6424130	
	(1.42)		(0.79)		(-0.52)		(0.45)		(-0.34)		(-0.26)		(-0.37)	
Ln(*RHO*)	-879.7	-	1434.9	*	203.1		578.4		-373.1		-1448.3		107.3	
	(-0.91)		(2.43**)		(0.10)		(0.32)		(-0.48)		(-0.41)		(0.60)	
Ln(*VAR*) ×Ln(*RHO*)	-6210160	-	-480435		1918890	*	539989		826705		-1325890		997287	
	(-1.40)		(-0.73)		(0.94)		(0.47)		(0.25)		(-0.27)		(0.40)	
Ln(*GAMMA*)	-2.22	-	12.51	**	-0.50		-2.41		-0.40		4.01		-0.26	
	(-0.64)		(2.46**)		(-0.09)		(-0.34)		(-0.88)		(0.36)		(-0.55)	
Ln(*VAR*) ×Ln(*GAMMA*)	-63773000	-	-11381800		5045170		-7545880		5745160		1997960		2789160	
	(-1.42)		(-0.79)		(0.52)		(-0.45)		(0.34)		(0.26)		(0.37)	
Ln(*RHO*) ×Ln(*GAMMA*)	382.1	-	-623.2	*	-88.2		-251.2		162.1		629.1		-46.6	
	(0.91)		(-2.43**)		(-0.10)		(-0.32)		(0.48)		(0.41)		(-0.60)	
Commercial Banks (derived)														
Constant	241.18	-	12.19	-	19.94	-	270.14	-	-92.85	-	325.46	-	16.38	-
	(1.42)		(0.04)		(0.08)		(1.14)		(-1.21)		(0.44)		(0.44)	
Ln(*ALFA*)	1.39	-	-0.66		3.45		0.23		0.79		1.35		-0.40	
	(0.44)		(-0.30)		(0.79)		(0.02)		(0.36)		(0.37)		(-0.86)	
Ln(*DIST*)	0.004	-	-0.001		-0.003		0.007		0.017		-0.016		0.004	
	(0.32)		(-0.08)		(-0.15)		(0.26)		(1.02)		(-0.70)		(0.80)	
Ln(*DtD*)	-0.239	-	0.161		-0.001		-0.119		-0.174		0.328		-0.050	
	(-0.85)		(0.50)		(0.00)		(-0.25)		(-0.49)		(0.81)		(-0.39)	
Ln(*VAR*)	11858700	-	-1085850		7237970		17375400		-8800950		-4258970		-1128730	
	(1.38)		(-0.62)		(0.54)		(0.45)		(-0.91)		(-0.53)		(-2.19**)	
Ln(*RHO*)	4309.6	-	4457.4		-22135.1		2790.7		15049.2		58513.8		908.2	
	(0.15)		(0.25)		(-0.34)		(0.08)		(0.61)		(0.55)		(0.18)	
Ln(*VAR*) ×Ln(*RHO*)	-175435	-	-4085.09		3900.34		144924		1367960	**	31023.8		79936.3	
	(-0.97)		(-0.08)		(0.06)		(0.31)		(1.93*)		(0.08)		(3.55***)	
Ln(*GAMMA*)	-104.51	-	-5.46		-8.66		-117.21		40.49	*	-141.66		-7.07	
	(-1.42)		(-0.04)		(-0.08)		(-1.15)		(1.21)		(-0.44)			
Ln(*VAR*) ×Ln(*GAMMA*)	-5150080	-	471653		-3143480		-7545880		3822620		1849890		489880	
	(-1.38)		(0.62)		(-0.54)		(-0.45)		(0.91)		(0.53)		(2.19**)	
Ln(*RHO*) ×Ln(*GAMMA*)	-1871.9	-	-1935.9		9613.1		-1211.6		-6535.6		-25412.2		-394.3	
	(-0.15)		(-0.25)		(0.34)		(-0.08)		(-0.61)		(-0.55)		(-0.18)	

Table 6. (continued)

Sector / Regressor	Manufacturing		Construction		Transport-Commun.		Trade		Real Estate		Services		Other	
	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.	Estimate	Wald t.
Credit Cooperatives (derived)														
Constant	-3.97	-	6.56	-	26.35	-	-4.52	-	1.12	-	-4.47	-	1.55	-
	(-1.56)		(1.94*)		(6.04***)		(-1.01)		(1.27)		(-0.58)		(4.32***)	
Ln(*ALFA*)	-1.17	-	-1.50		0.05		-14.72	**	1.17		-0.44		0.23	
	(-1.04)		(-1.34)		(0.06)		(-2.30**)		(0.91)		(-0.24)		(1.20)	
Ln(*DIST*)	0.042	-	0.021		0.128	***	-0.037	***	0.037		0.005		0.030	
	(2.49**)		(1.08)		(6.93***)		(-1.43)		(2.04**)		(0.22)		(4.23***)	
Ln(*DtD*)	0.253	-	0.166		-0.030	***	0.359		-0.034	***	0.085	*	-0.043	***
	(4.91***)		(2.90***)		(-0.52)		(4.48***)		(-0.60)		(1.20)		(-1.91*)	
Ln(*VAR*)	-9.39×10^{10}	-	-7.78×10^{10}		2.72×10^{12}		-3.33×10^{12}		9.38×10^{9}		-3.39×10^{11}		-1.42×10^{10}	
	(-0.23)		(-0.29)		(0.53)		(-0.73)		(0.53)		(-1.66*)		(-0.27)	
Ln(*RHO*)	341.6	-	-338.1	*	4240.7	***	-637.5		-93.0		120.5		256.1	
	(1.10)		(-1.90*)		(6.06***)		(-1.23)		(-0.33)		(0.11)		(4.49***)	
Ln(*VAR*) ×Ln(*RHO*)	-4.86×10^{9}	-	6.52×10^{10}	*	-4.39×10^{9}		2.35×10^{9}		-2.06×10^{10}		-4.58×10^{10}		4.00×10^{9}	
	(-0.20)		(2.71***)		(-0.46)		(0.58)		(-0.77)		(-1.40)		(0.68)	
Ln(*GAMMA*)	1.43	-	-3.04	**	-11.54	***	1.63		-0.49	*	1.85		-0.66	*
	(1.30)		(-2.05**)		(-6.13***)		(0.83)		(-1.32)		(0.55)		(-4.43***)	
Ln(*VAR*) ×Ln(*GAMMA*)	4.08×10^{10}	-	3.35×10^{10}		-1.18×10^{11}		1.45×10^{11}		-4.07×10^{9}		1.47×10^{11}		6.16×10^{9}	
	(0.23)		(0.29)		(-0.53)		(0.73)		(-0.52)		(1.66*)		(0.27)	
Ln(*RHO*) ×Ln(*GAMMA*)	-148.3	-	146.9	*	-1841.9	***	276.8		40.5		-53.1		-111.2	
	(-1.10)		(1.90*)		(-6.06***)		(1.23)		(0.33)		(-0.11)		(-4.49***)	
R-squared	0.14		0.06		0.21		0.25		0.07		0.15		0.17	

Notes:

1. The table reports parameters estimated over the differenced data (= FY2003 levels minus FY2002 levels). The total number of observations is 381.
2. For other notes refer to Table 4.

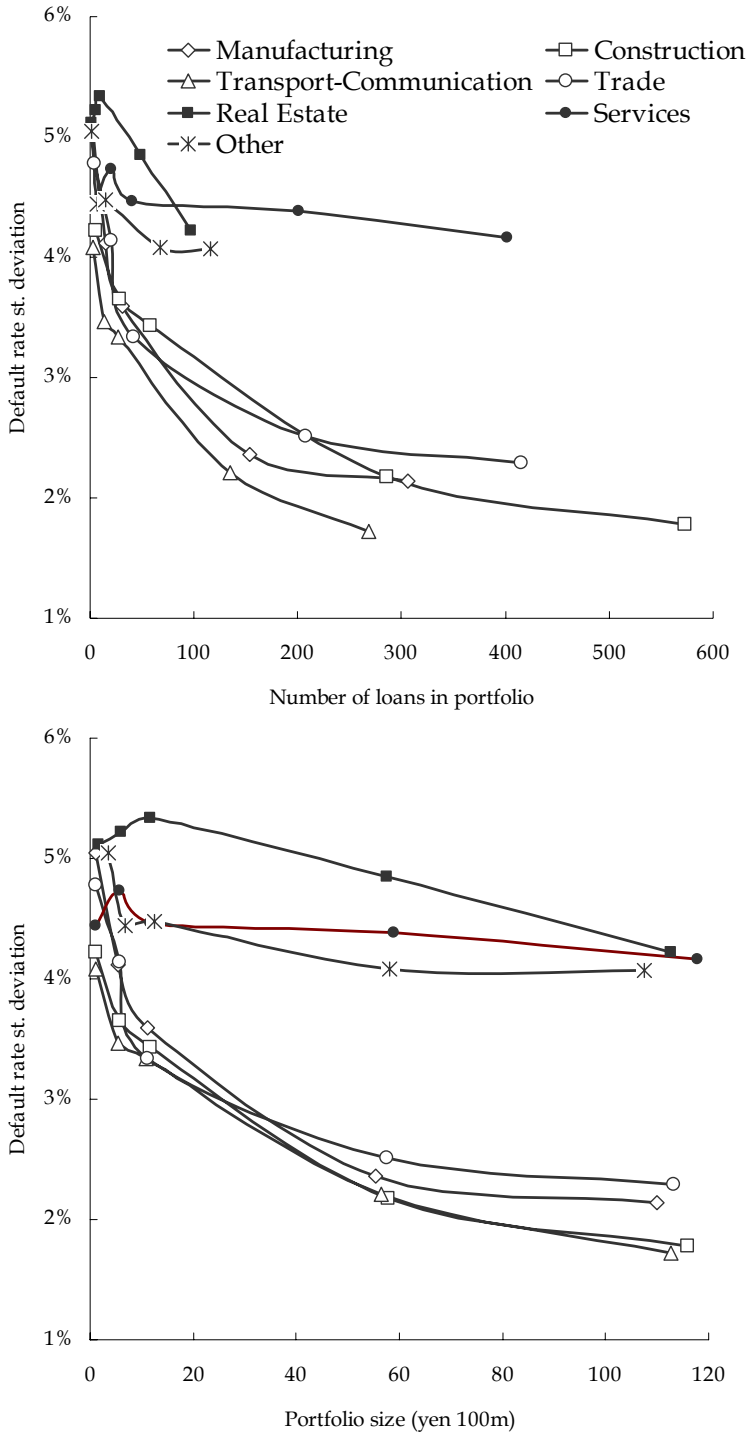

Figure 1. Default rate variability by portfolio size

The figure plots changes in the default rate variability by portfolio size. Based on the averages of variance estimates for hypothetical loan portfolios (sector/region/year) randomly generate from the CRD data. For further details refer to Appendix II.