Credit Concentration and Cyclical Economic Capital of Loan Portfolios

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ABSTRACT

This paper proposes a framework to analyze concentration risk of loan portfolios by quantifying the amount of economic capital (EC) throughout an economic cycle. The empirical investigation using the Bank of Thailand's default data demonstrates that credit concentration risk is a major cause of an extreme credit portfolio loss event faced by commercial banks that conduct relationship-lending business. It shows that five major industries of aggregate national loan portfolios are highly exposed to the same common risk factors, in addition to the macroeconomic risk factors that drive the default rate. The findings suggest that an estimate of the time-varying risk level in the Thai loan market is important to: (i) policy makers as they design the appropriate level of regulatory capital, (ii) credit portfolio managers because they likely identify medium and long-term business plans, and (iii) risk managers because they need to predict short- and long-term default risk in their credit portfolios in order to set out an effective risk mitigation plan.

Keywords: Credit Risk, Credit Modeling, Loan Portfolios, Economic Capital, Concentration Risk

บทคัดย่อ

งานวิจัยฉบับนี้เสนอกรอบการประเมินความเสี่ยงกระจุกตัวของพอร์ตสินเชื่อ โดยประเมินเงินกองทุนทางเศรษฐศาสตร์ตลอดวัฐจักรของเศรษฐกิจ ผลการศึกษาเชิงประจักษ์โดยใช้ข้อมูลการผิดนัดชำระหนี้จากธนาคารแห่งประเทศไทยสาธิตให้เห็นว่าความเสี่ยงด้านกระจุกตัวด้านเครดิตเป็นสาเหตุหลักของเหตุการณ์การสูญเสียอย่างรุนแรงของมูลค่าพอร์ตการให้กู้ยืมด้านสินเชื่อของธนาคารพาณิชย์ การศึกษาแสดงให้เห็นว่าห้าอุตสาหกรรมหลักของประเทศเปิดเผยถึงความเสี่ยงร่วม ซึ่งเป็นปัจจัยขับเคลื่อนการผิดนัดชำระหนี้นอกเหนือไปจากความเสี่ยงอันเนื่องมาจากปัจจัยทางเศรฐศาสตร์มหภาค ผลการศึกษาแนะนำว่าประมาณการระดับความเสี่ยงในตลาดสินเชื่อของประเทศไทยมีความสำคัญดังนี้: (1) ผู้กำหนดนโยบายในการกำหนดเงินกองทุนที่เหมาะสม, (2) ผู้จัดการพอร์ตเครดิตในการระบุแผนธุรกิจในระยะกลางและระยะยาว และ (3) ผู้จัดการด้านความเสี่ยงในการวางแผนจัดการด้านความเสี่ยงที่มีประสิทธิภาพ

คำสำคัญ: ความเสี่ยงด้านเครดิต, แบบจำลองด้านเครดิต, พอร์ตสินเชื่อ, เงินกองทุนทางเศรษฐศาสตร์, ความเสี่ยงเชิงกระจุกตัว

INTRODUCTION

Concentration risk of loan portfolios is defined as the risk of a substantial loss of capital value from the defaults of loans in any portfolios, which happen simultaneously under a distress event, because each portfolio has high exposure to a single risk factor that drives the simultaneous default events of the loans in those portfolios. An aggregated portfolio of multiple sub-portfolios, each without single-name concentration, may exhibit risk factor concentration and demonstrate a large extreme loss during a downturn as each sub-portfolio exposes to the same common factor. The knowledge of risk factor exposure of each sub-portfolio is important for planning a diversified total portfolio. Non-diversified loan portfolios face concentration risk that could jeopardize the portfolio value by a huge principal loss from a severe economic crisis. Contrasting with the diversified portfolio, the highly concentrated loan portfolio potentially undermines

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bank shareholders' value creation, as its wealth is less sustainable due to a highly volatile loss during an economic downturn. In addition, the bank may be less capable of granting new profitable credit during the boom period. Assessing the concentration level facilitates portfolio managers to perform efficient capital allocation and lending decisions. Evaluating the economy-wide concentration level of credit risk provides useful suggestions to policy makers to implement some appropriate macro-prudential regulations (such as additional capital reserve requirements), as well as to economists to gauge the health of credit in the aggregate economy. This study is motivated by the regulation mandated by the BCBS (2006) that requires banks to assess concentration risk and their available capital to ensure that the banks do not exceed the appropriate concentration limit. Practitioners and academics employ various credit portfolio models for credit portfolio management (Merton, 1974; Lando, 1998; Shumway, 2001; Vasicek, 2002; Carling, Jacobson, Linde, & Roszbach, 2007; Das, Duffie, Kapadia, & Saita, 2007). However, there is none in the large body of literature providing an evaluation of the concentration risk in terms of the extra capital requirement to absorb large abnormal losses across a variety of economic scenarios, as well as its prominent impact on the profitability and sustainability of the commercial banking systems. This study, therefore, aims at answering this question by examining the implication of concentration risk on the level of an excessive portfolio loss from the default of a loan portfolio throughout the economic cycle. The required capital reservation reflecting the level of risk the bank has undertaken has implications to equity holders and borrowers. Available capital in excess of the requirement benefits the bank by obtaining a higher credit rating and acquiring a lower cost of funds compared to banks with tight capital cushions. As a result, this benefits the borrowers by providing a lower borrowing rate. Banks with competitive costs of funds through their high creditworthiness are more profitable in the competitive lending market.

Due to the asymmetric return behavior of credit risk with a limited upside from an interest revenue but an unlimited downside from a principal loss, the cost and revenue structure of commercial banks as financial intermediaries is distinguished from that of corporations. Importantly, credit risk is a major source of risk for commercial banks pursuing a large proportion of investment in the relationship-lending business. According to Merton and Perold (1996), commercial banks have several unique characteristics. First, the banks' operations are opaque in the equity holders' view, making the cost of raising new equity higher than the cost of internal equity. This implies that banks are not able to freely raise capital, especially during bad economic regimes, as capital becomes costly when it is needed most. Second, banks' creditworthiness is affected by the credit qualities of the assets in their portfolios. Froot and Stein (1998) pointed out that the information cost of assessing the level of credit risk in bank investment portfolios causes the equity capital to become more costly. Consequently, managing such risk is crucial to the bank's stability. Last, banks operate in highly competitive lending and funding markets. As a result, their creditworthiness determines their cost of funds and the level of profitability acquired from underwriting the loans or any instruments exposed to credit risk. For example, in the circumstance without deposit insurance, the higher credit rating allows a bank to raise funds with a lower deposit rate and to be more competitive, as its cost of funds is lower. The amount of available equity capital is a key determinant of the bank's credit rating, as it is the quality capital absorbing the loss from the default of credit investment portfolios in order to ensure a full payment of principle to the bank's creditors. As it is mandated by the regulatory body as well as forced by market discipline, maintaining sufficient equity capital associated with the level of risk inherent in the investment portfolio is necessary for a bank to secure its on-going operations. To be more precise, banks are expected to reserve enough capital at risk, which is the minimum amount of available capital to buffer the loss from investment beyond the expected loss. The value of capital at risk is generally known as economic capital (EC). The amount of available capital in excess of the required capital at risk is a measure determining the solvency of the bank—its ability to keep the promise to repay the funds to its own creditors. In addition, it helps banks to stay competitive by making the cost of funds cheaper than lower-rated banks. Berger, Herring, and Szego (1995) discussed the role of bank capital in value creation and pointed out that banks hold capital in excess of regulatory requirements to create competitive advantage.

Allen, Carletti, and Marquez (2011) provided empirical evidence suggesting that a bank is undercapitalized relative to social-welfare optimizing levels, although it holds capital in excess of regulatory capital. It shows that the undercapitalized capital of the financial system leads to financial crises. Funding liquidity shortage due to bank credit deterioration leads banks to cut lending (Ivashina & Scharfstein, 2010). Hence, loan supply and capital sufficiency are closely related. On the contrary, profitable lending and the low cost of raising capital increase a bank's risk taking capacity and help the bank build up capital (Calomiris & Kahn, 1991) to create more business opportunity. The empirical results supporting this argument include the work by Košaket, Li, Lončarski, and Marinč (2015). Therefore, capital adequacy is crucial for the stability of the financial system at the macro level and for any bank's on-going operations at the micro level.

This article contributes to the existing literature in three folds. First, it is the first study that estimates the regime dependent risk at the industry level of the entire Thai economy by offering an industry level credit risk model that links macroeconomic variables. The study is also capable of measuring capital at risk by industry at a point in time throughout the business cycle. The model takes into account the diversification of credit risk within the same industry, as the data are taken from the total industry-country level. Second, it demonstrates that the country's credit market is subject to concentration risk in which all selected industries expose to the same risk factor. To obtain this assessment, I apply the contemporary approach in literature to answer my research questions. Precisely, the model extension of Jakubik and Schmieder (2008) from the currently well accepted single-factor credit risk model, namely the asymptotic single-risk factor proposed by Vasicek (2002), creates the linkage between economics variables and risk factors determining a regime-dependent risk capital quantification at the portfolio level. I show that the model of Jakubik and Schmieder (2008) can be applied with the parsimonious implementation approach to analyze the degree of concentration risk in the economy. This is a simpler alternative to the multifactor type of the structural model, utilized by many (Demey, Jouanin, Roget, & Roncalli, 2004; Pykhtin, 2004), and other types of both structural and actuarial models (Altman & Saunders, 1997; Crouhy, Galai, & Mark, 2000; Gordy, 2000; Duffie & Singleton, 2003). The application of my approach provides the first study of evaluating the factor sensitivity of the cyclical capital concentration at the sectorial level. The study also offers a framework for the predictability of the turning direction of required capital upon a regime change, which can benefit regulators in setting a macro prudential policy, for example, Lim, Columba, Kongsamut, Saiyid, & Wu (2011), and financiers in strategic portfolio management. Third, I conduct an empirical analysis on what level of concentration risk (i.e., the size of factor loading) in the loan market can cause a large loss in credit portfolio during a bad economic regime.

In what follows, I discuss the methodology concerning the well-known structural model as the theoretical framework in my study and the parameter estimation approach. I use historical data of default rates from the Bank of Thailand reported by commercial banks operating in Thailand. Based on the estimated model, I conduct a scenario analysis to demonstrate how the required capital at risk varies by the economic scenarios. Finally, I test the hypothesis of the effect of concentration risk on the losses of loan portfolios and conduct factor sensitivity to show how the factor concentration plays an important role in quantifying demanded capital throughout the economic cycle.

METHODOLOGY

Due to its broad implications to portfolio management including capital allocation, portfolio risk management, and the pricing of credit portfolio instruments as well as its nice features to describe the default mechanism, the structural model family, first developed in a single-factor framework by Merton (1974) and further by Vasicek (2002), has been adopted widely by financial institutions. Several extended versions into multifactor frameworks are widely used by credit portfolio managers from Moody's, CreditMetrics, J.P. Morgan, and many others as discussed in Crouhy et al. (2000) and Altman and Saunders (1997). Both assume that a borrower defaults if the value of his or her assets at maturity falls below the obligation value. Though its default mechanism is insightful and simple, the structural model posits a challenging implementation issue. This involves the estimation of the model parameters, such as the asset return correlation and the default boundary. It is generally known that the asset value and default boundary are not observable because the market data are not available. Therefore, most practitioners and researchers, for example, Crosbie and Bohn (2003) and Bharath and Shumway (2008), acquire inference on asset values from the market values of equities and use them for parameter calibration. The requirement of a marketable value of equity is not applicable for the use of this approach in estimating the portfolio model where the obligors are non-listed firms. Nonetheless, equity inferred asset correlation estimation is not straightforward, and it requires a numerical procedure.

My approach adopts the framework from Vasicek (2002) and Jakubik and Schmieder (2008) to construct a model that addresses the above-mentioned calibration issues. Consequently, the calibrated models I propose here serve the objective of this study for a concentration risk investigation. There are several multifactor models providing the risk capital quantification for the loan with non-homogenous credit in terms of the size of loan outstanding in the portfolio, for example, Pykhtin (2004), and Gordy and Lütkebohmert (2013). However, those models are based on the assumption that each loan in the portfolio has a large exposure. Moreover, these models start with the multifactor framework and provide an adjustment to obtain an approximate analytical closed-form solution. My approach is different from these studies in two aspects. First, my approach does not rely on the assumption of having a large size of loan outstanding of any loan, and I will show that a portfolio without a large outstanding exposure of the portfolio constituents may exhibit a large risk factor exposure. Second, my approach starts with the single risk factor model in which it immediately provides the analytical closed-form solution. I then decompose such a risk factor into multi-factors, which are shared across portfolios. I evaluate the risk factor concentration without providing an approximation through the adjustment term. I argue that my approach is suitable to evaluate the degrees of concentration risk exposed by each industrial loan portfolio of the total country. My analysis focuses on identifying the concentration risk of the overall economy due to the concentration to a single risk factor exposure faced by each industry without the required assumption of the total loan outstanding of each industrial country loan portfolio. I examine the effects of this risk to the portfolio loss at the industry level without quantifying the total country value at risk. However, the models developed by Pykhtin (2004) and Gordy and Lütkebohmert (2013) are more appropriate for assessing capital at risk of the aggregated loan portfolio when loans are non-identical in sizes and in credit risk model parameters.

Let L_j denote the portfolio loss of a homogeneous portfolio of industry j, where the portfolio has $\widehat{K}_j$ homogeneous loans of equal notional amount in the portfolio. Assume that the notional amount of each loan is $\widehat{K}_j$. Assuming the loss given default is equal to one, L_j is given by:

$$L_j = \sum_{i=1}^{\widehat{K}_j} \tilde{L}_{ij} ,$$

where $\tilde{L}_{ij}$ is $1/\widehat{K}_j$ if loan i in industry j defaults or 0 if loan i in industry j does not default. The i^{th} borrower's assets in a portfolio of the industry j, denoted by A_{ij}, follows the geometric Brownian motion

$$dA_{ij} = \mu_j A_{ij} dt + \sigma_j A_{ij} dW_{ij}, \tag{1}$$

where W_{ij} is the standard Weiner process , μ_j is drift and σ_j is volatility.

Since the portfolio j is homogeneous, all loans in the portfolio share the same drift, μ_j, and volatility, σ_j, of asset return dynamic and the same economic dependent default boundary $B_j(T|x)$, which is the obligation of the representative borrower to pay in portfolio of industry j at time T and x is an m-dimensional vector of economic variables at time T. The time interval T is the risk measurement horizon. At time T, the i^{th} borrower defaults with probability

$$p_{ij} = P\left[A_{ij}(T) < B_j(T|x)\right]. \tag{2}$$

Let us specify $B_j(T|x)$ as follows:

$$B_j(T|x) = \alpha_j e^{\sigma_j \sqrt{T} \beta_j{}' x}, \tag{3}$$

where β_j is an m-dimensional vector of coefficients, and α_j is some constant parameter representing the debt obligation of any borrower i in portfolio of the industry j. I characterize the ability of the i^{th} borrower to repay through the stochastic variables $A_{ij}(T)$ and $B_j(T|x)$. These two variables describe three key components of credit quality, which are the level of debt obligation α_j, the economic factors, x, and the wealth of the borrower $A_{ij}(T)$. The economic factors are for qualitative adjustment of the representative borrower of the portfolio j throughout the economic cycle, which may reflect the willingness to pay, the potential of revenue-generation of other assets, and the potential change in financial obligation to other financial liabilities besides those indicated by the loan contract.

The econometric representation of (1) is given by:

$$logA_{ij}(T) = logA_{jo} + \mu_j T - \frac{1}{2}\sigma_j^2 T + \sigma_j \sqrt{T} U_{ij}, \tag{4}$$

where U_{ij} is a standard normal random variable for loan i in industry j. By (2) and (4), I obtain the following:

$$p_{ij}(x) = P\left[A_{ij}(T) < B_j(T|x)\right] = P\left[U_{ij} < \frac{log\alpha_j - logA_{jo} - \mu_j T + \frac{1}{2}\sigma_j^2 T}{\sigma_j\sqrt{T}} + \beta_j{}'x\right] \quad (5)$$

$$p_{ij}(x) = \Phi\left(c_j + \beta_j{}'x\right), \quad (6)$$

where $\Phi(\cdot)$ is the cumulative probability distribution function of a standard normal random variable and c_j is the static component of default boundary and is given by:

$$c_j = \frac{log\alpha_j - logA_{jo} - \mu_j T + \frac{1}{2}\sigma_{ij}^2 T}{\sigma_j\sqrt{T}}. \quad (7)$$

Note that $p_{ij}(x)$ does not depend on i because all the loans in similar risk classes are identical in their default characteristics. The standard normal random variable U_{ij} is jointly standard normal with equal pairwise correlation $\sqrt{\rho_j}$ with the common risk factor Y_j of the industry j and $\sqrt{1-\rho_j}$ with the idiosyncratic risk factor Z_{ij}, where Z_{ij} and Y_j are independent. Therefore, U_{ij} is given by:

$$U_{ij} = Y_j\sqrt{\rho_j} + Z_{ij}\sqrt{1-\rho_j}. \quad (8)$$

Conditional on Y_j, the probability of default of i in j is:

$$P\left[L_{ij} = 1\middle|Y_j, x\right] = \Phi\left(\frac{c_j + \beta_j{}'x - Y_j\sqrt{\rho_j}}{\sqrt{1-\rho_j}}\right), \quad (9)$$

The number of defaults of portfolio j follows the binomial distribution with ters $P\left[L_{ij} = 1\middle|Y_j, x\right]$ and $\widehat{K}_j$.

By the law of large numbers and with the loss given default equal to one, the portfolio loss amount approaches probability of default revealed in equation (9). This assumption is held for large homogeneous loan portfolios. It is clear that the risk factors determining the time-varying portfolio loss rates are macroeconomic variables x and unobservable (latent) risk factors Y_j. Equation (9) is equivalent to equation (3) demonstrated in Vasicek (2002) and equation (4) in Jakubik and Schmieder (2008) with the modification of the additional term $\beta_j{}'x$. Therefore, with similar derivation as in Vasicek (2002) under the assumption of an infinitely fine-grained homogenous loan portfolio, the cumulative loss distribution function $F(\cdot) = P(L_j \le l|x)$ of the portfolio of industry j and its density function $f(\cdot)$ are given by:

$$F\left(l; c_j, \rho_j, \beta_j\middle|x\right) = \Phi\left(\frac{\sqrt{1-\rho_j}\Phi^{-1}(l) - \Phi^{-1}(c_j) - \beta_j{}'x}{\sqrt{\rho_j}}\right), \quad (10)$$

$$f\left(l; c_j, \rho_j, \beta_j\middle|x\right) \quad (11)$$
$$= \sqrt{\frac{1-\rho_j}{\rho_j}}\exp\left(-\frac{1}{2\rho_j}\left(\sqrt{1-\rho_j}\mathit{\Phi}^{-1}(l) - \mathit{\Phi}^{-1}(c_j) - \beta_j{}'x\right)^2 + \frac{1}{2}\left(\mathit{\Phi}^{-1}(l)\right)^2\right),$$

where l is the portfolio loss rate. The loss at the q-quantile of the loss distribution function is given by:

$$L_{qj}|x = F\left(q; 1-c_j, 1-\rho_i, -\beta_j\middle|x\right). \quad (12)$$

The proofs of (10) through (12) are demonstrated in Appendix A.

Assume that the common risk factor $Y = (Y_1, Y_2 \dots . Y_J)'$ are jointly normal and are independent of Z_{ij} for any loan i and industry j , I represent $Y = (Y_1, Y_2 \dots . Y_J)'$ by J mutually independent common risk factors $\widehat{Y} = (\widehat{Y_1}, \widehat{Y_2}, \dots \widehat{Y_J})'$. Therefore, each industry common risk factor Y_j is decomposable into J principal factors by the principal component decomposition method as follows. The vector $Y = (Y_1, Y_2 \dots . Y_J)'$ satisfies the following system of equations.

$$Y = C\widehat{Y}, \tag{13}$$

where $\widehat{Y} = (\widehat{Y_1}, \widehat{Y_2}, \dots \widehat{Y_J})'$ is the vector of principal components of Y and C is the J by J matrix of principal component coefficients, which is the matrix of the column eigenvector of the covariance matrix of Y. Let the first principal component $\widehat{Y_1}$ represent the component with the highest variance of all components, and the second principal component $\widehat{Y_2}$ represent the component with the second largest variance, and so on. Therefore, equation (8) can be written as:

$$U_{ij} = \sqrt{\rho_j} C_j \widehat{Y} + Z_{ij}\sqrt{1 - \rho_j}, \tag{14}$$

where C_j is the norm vector taken from the j^{th} row of C and the k^{th} element in the vector of factor loadings with $\sqrt{\rho_j} C_j$, denoted by v_{kj}, specifying the risk exposure of the portfolio of industry j to risk factor k.

Let $V_{kj} = (v_{1j}, \dots, v_{k-1,j}, v_{k+1,j}, \dots, v_{J,j})$ and $\| V_{kj} \|$ be the norm of V_{kj}. Consequently, the single common risk factor model (1) has its equivalent multifactor form. Conditional on x and $\widehat{Y_k}$, the cumulative loss distribution function is given by:

$$\bar{F}\left(L_q; c_j, \sqrt{1-\rho_j}, \| V_{kj} \|, v_{kj}, \beta_j, \middle| \widehat{Y_k}, x_,\right) = \Phi\left(\frac{\sqrt{1-\rho_j}\Phi^{-1}(l) - \Phi^{-1}(c_j) - \beta_j' x + v_{kj}\widehat{Y_k}}{\| V_{kj} \|}\right). \tag{15}$$

The proof of (15) is similar to the proof of (10) in Appendix A. Equation (15) allows us to solve the conditional loss quantile using the relationship in (13) in order to study the implication of risk factor concentration (v_{kj}) on high loss quantiles. The conditional loss quantile of portfolio j on the k^{th} principal component and economic variables x is given by:

$$\overline{L_{qJk}} | \, x = \bar{F}\left(q; 1 - c_j, \| V_{kj} \|, \sqrt{1-\rho_j}, -v_{kj}, -\beta_j \middle| \widehat{Y_k}, x\right). \tag{16}$$

The proof is provided in Appendix B. The portfolio loss quantile conditional on the first principal component, $\bar{F}\left(q; 1 - c_j, \| V_{kj} \|, \sqrt{1-\rho_j}, -v_{1j}, -\beta_j x \middle| \widehat{Y_1}, x\right)$, can be interpreted as a EC at a q confident interval by industry j under a particular economic regime described by a state vector $[\widehat{Y_1}, x]$.

To estimate the parameters of each portfolio j for the unknown parameters β_j, c_j, ρ_j by choosing the parameters that maximize the log-likelihood function of the form:

$$\max_{\beta_j, c_j, \rho_j} \sum_{n=1}^{N} (\log\left(f\left(l_{jn}; c_j, \rho_j, \beta_j \middle| x_n\right) \cdot g(x_n | x_{n-1}, \dots x_0)\right), \tag{17}$$

where $g(x_n|x_{n-1}, \dots x_0)$ is the probability density function of state vector x_n conditional on the entire historical values $x_{n-1}, \dots x_0$ and N is the number of observations, and the likelihood function $f(l_{jn}; c_j, \rho_j, \beta_j | x_n)$ is given by (11). Since the first order condition of (17) does not involve $g(x_n|x_{n-1}, \dots x_0)$, (17) can be reduced to[1]

$$\max_{\beta_j, c_j, \rho_j} \sum_{n=1}^{N} \log (f(l_{jn}; c_j, \rho_j, \beta_j | x_n). \tag{18}$$

Note that Jakubik and Schmieder (2008) maximized the likelihood of binomial distribution of the number of defaults with probability characterized by (9). This approach requires the knowledge of the number of credits in each period as well as the need for numerical integration to integrate out the latent variable in (9). The proposed approach does not require numerical integration and the default data at the loan level. The implementation is thus simpler and more economical.

EMPIRICAL ANALYSIS, RESULTS AND DISCUSSION

The Data

The historical default data of five industrial portfolios were obtained from the Bank of Thailand for parameter estimation and empirical analysis. These include agriculture, manufacturing, commerce, real estate, and personal consumption. The first four of the five portfolios are loans to corporations, while the last one is a retail loan portfolio. The data cover the period from the third quarter of 2001 to the fourth quarter of 2014. The five industries out of ten are selected based on the following criteria: (i) non-financial industry, (ii) industry with similar business characteristics, and (iii) non-state-own or government support business industry. The service industry includes various types of businesses, including, but not limited to, hospitals, hotels, education and entertainment. Hence, this industry is not appropriate with the homogeneity of the loan portfolio assumption. The utilities industry includes large state-own businesses or those with substantial government supports; therefore, their default behaviors cannot be explained only by the economic factors. The construction sector is not included since it is an industry related to real estate. The correlation between the construction sector and the real estate industry is at 0.78, which is the highest among any portfolio pair, and their businesses are closely related. The mining and quarrying sector is also excluded because it is an industry producing the upstream raw materials demanded by other industries. The health of the industry thus depends on the strength of the others, especially the commerce industry as their correlation is as high as 0.71. Although the personal consumption loan does not exhibit any single name concentration (that is, the outstanding amount of each loan is not large), they may exhibit the risk factor concentration which exposes to the same risk factors as those exposed by the commercial credit. I include this sector to show that the inclusion of the personal consumption loan subportfolio to the total loan portfolio with the pre-existing commercial loan portfolios may increase the level of concentration risk, instead of getting the diversification benefit, as they expose to the same risk factor.

[1] See Hayashi (2000) for conditional maximum likelihood estimation.

TABLE 1

Descriptive Statistics of Default Rate Behaviors

Industry	Mean (%)	S.D. ($x10^{-2}$)	Skewness	Kurtosis
Agriculture	1.63	1.17	1.68	6.55
Manufacturing	1.36	0.80	0.87	3.70
Commerce	1.13	0.74	1.25	4.46
Real Estate	1.43	1.22	1.76	6.46
Personal Consumption	0.95	0.48	1.78	6.21

TABLE 2

Descriptive Statistics of Selected Economic Variables

Economic Variables	Mean	S.D.	Skewness	Kurtosis
GDP	3.97	4.33	-0.22	6.26
SET	5.26	11.17	-0.49	4.85
UMP	1.44	0.71	0.75	2.68
MPI	1.77	4.79	-0.39	3.64
FX	0.72	2.00	0.31	2.80
INF	1.27	0.93	0.23	2.68
RIR	1.63	0.55	0.29	2.50

Note: The quarterly economic data are taken from Bank of Thailand, Bloomberg, and Thomson Reuters. Unemployment (UMP), real interest rate (RIR), foreign exchange rate index (FX), and manufacturing production index (MPI) are from Bank of Thailand. Headline Inflation (INF) and GDP are from Thomson Reuters. SET index is from Bloomberg. The symbols GDP, SET, FX, and MPI represent the change versus one year ago in the logarithm of the value. The data cover from the 3rd quarter of 2001 to 4th quarter of 2014.

The chosen economic variables are as follows: (i) real gross domestic product (GDP) growth rate representing the direction of economy, (ii) stock market index return representing the financial market condition, (iii) unemployment rate reflecting the health of the economy, (iv) manufacturing production index (MPI) as an indicator of the cyclical growth of an economy, (v) exchange rate index determining competitive advantage of country's export, (vi) inflation as an indicator of the stage of economic cycle, and (vii) real interest rate indicating the financial cost to corporate investments. Because nominal income incorporates inflation, the information regarding the level of inflation and real income (through GDP measure) captures the nominal income completely. Assuming the role of credit on the growth of property prices, the theoretical model of McQuinn and O'Reilly (2008) captures the important roles of the interest rate and disposable income indicative of the lending capacity as the key determinants in the boom and bust in property prices. Therefore, the real interest rate, inflation, and GDP are inferable to the level of the property price index. Nominal income and the housing price index are excluded in this analysis for the aforementioned reason. The GDP and unemployment rate are regarded as fundamental to the default rate in the literature (Jakubik & Schmieder, 2008; Figlewski, Frydman, & Liang, 2012). It is well known that the level of stock prices is a leading indicator of economic status, and it has been taken as a macro-economic covariate in default risk modelling (Bharath & Shumway, 2008; Duffie, Eckner, Horel, & Saita, 2009; Giesecke & Kim, 2011; Lando & Nielsen, 2010). Tables 1 and 2 report descriptive statistics of default rates and economic variables. The default characteristics of five industrial loan portfolios exhibit positive skewness showing that high default loss is highly likely, and positive kurtosis higher than three indicating that the loss distribution has a fat-tail in which the loan portfolios are subject to tail risk. The skewness and kurtosis of all the economic variables except GDP are close to zero and three respectively, demonstrating that they distribute closely to a normal distribution. The pairwise correlations of economic variables are shown in Tables 3-6. The trend and cyclical components of each economic variable is filtered from the time series data of each economic variable using Hodrick-Prescott filter.[2] The time series correlations between the trend components and the default rates are shown in Table 5, and those between the cyclical components and the default rates are shown in Table 6.

The correlations between the default rate and the economic variables are reported in Table 4. The data cover the period from the 3rd quarter of 2001 to 4th quarter of 2014, which is the entire duration of available data. The change in GDP and that in MPI are positively correlated with the default rate, while inflation is negatively correlated, which seems counterintuitive; however, these economic variables and the default rates are cyclical and auto correlated, which requires some lead time for the variables to take the effects (i.e., the drop in MPI may recede when the default rate is turning to peak). Since the policy maker targets inflation, a moderate inflation is a sign of a healthy economy, and this explains its negative relationship with the default rates. Note that the sign of the correlations between the economic variables and the default rates and between the trend component of economic variables and the default rates are the same except SET and FX. Both SET and FX are factors determining the risk in the financial market, which response quickly to the change in financial market conditions, and the signs of the correlations between these factors and the default rates are the same as those between the cyclical component of these factors and the default rates. This determines that the cyclical components of the economic variables representing the financial market condition are the factor driving the correlation between these variables and default rates.

TABLE 3

Time Series Correlation between Economic Variables

	GDP	SET	UMP	MPI	FX	INF	RIR
GDP	1	0.59	0.09	0.83	0.44	-0.12	-0.04
SET		1	-0.02	0.55	0.34	-0.31	-0.33
UMP			1	0.27	-0.07	-0.40	0.04
MPI				1	0.31	-0.27	-0.18
FX					1	0.05	0.23
RIR						1	0.36

TABLE 4

Time Series Correlation between the Portfolio Default Rate and Economic Variables

Industry	GDP	SET	UMP	MPI	FX	INF	RIR
Agriculture	0.10	-0.11	0.67	0.21	0.07	-0.25	0.32
Manufacturing	0.10	-0.19	0.67	0.28	-0.10	-0.31	0.14
Commerce	0.12	0.01	0.78	0.26	-0.03	-0.35	0.23
Real Estate	0.14	-0.05	0.56	0.21	-0.02	-0.17	0.10
Personal Consumption	0.03	-0.06	0.72	0.15	-0.01	-0.30	0.22

Note: There is no unit of measurement of GDP, SET, FX and MPI as they are indexed figures. The unit of measurement for inflation and interest rates is percentage. The symbols GDP, SET, FX, and MPI represent the change versus 1 year ago in the logarithm of the value. The log transformation of the indexes of GDP, SET, FX, and MPI is taken to standardize the variables, which are comparable to the percentage measure; therefore, the pair-wise correlation can be interpreted as the correlation of the percentage movement between two variables. The data cover from the 3rd Quarter of 2001 to 4th Quarter of 2014.

[2] See www.mathworks.com/help/econ/hpfilter.html.

TABLE 5

Time Series Correlation between the Portfolio Default Rate and the Trend Components of the Economic Variables

Industry	GDP	SET	UMP	MPI	FX	INF	RIR
Agriculture	0.57	0.15	0.70	0.61	0.03	-0.59	0.58
Manufacturing	0.67	0.13	0.73	0.74	0.15	-0.60	0.37
Commerce	0.75	0.45	0.90	0.72	-0.18	-0.86	0.68
Real Estate	0.65	0.24	0.68	0.62	0.07	-0.58	0.49
Personal Consumption	0.58	0.43	0.78	0.54	-0.30	-0.79	0.67

TABLE 6

Time Series Correlation between the Portfolio Default Rate and the Cyclical Components of the Economic Variables

Industry	GDP	SET	UMP	MPI	FX	INF	RIR
Agriculture	-0.06	-0.15	0.15	-0.07	0.07	-0.01	0.23
Manufacturing	-0.08	-0.23	0.09	-0.06	-0.14	-0.09	0.06
Commerce	-0.09	-0.09	0.02	-0.07	0.01	-0.01	0.10
Real Estate	-0.03	-0.11	-0.06	-0.08	-0.04	0.08	-0.01
Personal Consumption	-0.13	-0.17	0.09	-0.11	0.07	0.02	0.09

The Estimated Parameters and Filtered Risk Factors

The estimated parameters are reported in Table 7. The estimated parameters solve the inference problem (18). To identify the potential economic variables and their lags that lead to the problem (18), the univariate test of statistical significance using the likelihood ratio is conducted by comparing the likelihood obtained from the standard Vacisek's model and from the model with the additional economic factor. To identify the lag variable, the likelihood of each variable is compared against that of its own lag variable (the previous period data) and only the one with the highest value is chosen. The number of lags enters the likelihood ratio test is four for SET index, GDP, manufacturing production index, foreign exchange, inflation and the real interest rate. The number of lags enters the likelihood ratio test is two for the unemployment rate due to the limited historical data which are available from the 1st quarter of 2001. Instead of moving the data period to start in the 1st quarter of 2002 in order to have four periods lag data for an unemployment measurement, I choose the smaller number of lags to trade off to get the beginning period of the time series of default data the closest possible to the Thailand banking crisis in 1998.

Table 7 shows the estimation result from the set of variables chosen from the most significant lag variable of each economic variable from the univariate test. Almost all portfolios yield the significant result of UMP, MPI, INF, and RIR variables at 1% significance except personal consumption industry portfolios (in which only UMP, INF and RIR are significant), real estate (in which only UMP, MPI and RIR are significant), and inflation in manufacturing portfolio is significant at 10%.

The portfolio latent factor Y_j is filtered out using (9) by plugging in the historical default rate on the left-hand side of (9) and estimated parameters indicated in Table 7 and economic variables on the right-hand side. The time series Y_j of each portfolio are transformed to obtain the time series vectors of principal components. Table 8 depicts the correlations between principal components and the economic variables. The GDP and

SET are not significant in the univariate test. The FX is not significant in the multivariate model. This is because these economic variables exhibit low absolute correlation with all portfolio latent factors Y_j, which range from -0.02 to 0.15. In contrast, unemployment is the most significant variable that correlates with each latent factor Y_j ranging from 0.38 to 0.7 in absolute terms. Table 9 shows that the GDP and SET indexes exhibit low correlation with every latent factors and every principal component. In contrast, unemployment is highly negatively correlated with the first principal component, while inflation is positively correlated.

TABLE 7

The Estimated Parameters of Industry Loan Portfolios

Industry		**ρ** (x10^{-2})	**c** (x10^{-3})	UMP	MPI (x10^{-3})	INF (x10^{-3})	RIR
Agriculture		2.69***	3.33***	0.24***	6.75***	-36***	0.13***
	Std.Error	1.30×10^{-08}	5.81×10^{-04}	2.50×10^{-03}	1.19×10^{-03}	3.28×10^{-03}	3.28×10^{-03}
	lag			*0*	*3*	*0*	*4*
Manufacturing		3.04***	4.06***	0.21***	9.20***	-3.58*	0.05***
	Std.Error	1.42×10^{-08}	4.31×10^{-04}	2.25×10^{-03}	1.04×10^{-03}	2.41×10^{-03}	1.27×10^{-03}
	lag			*1*	*2*	*0*	*4*
Commerce		1.58***	2.46***	0.24***	5.89***	-30.32***	0.10***
	Std.Error	1.05×10^{-08}	3.68×10^{-04}	2.57×10^{-03}	9.57×10^{-04}	3.15×10^{-03}	1.27×10^{-03}
	lag			*1*	*2*	*0*	*4*
Real Estate		5.22***	2.73***	0.26***	7.26***		0.10***
	Std.Error	1.43×10^{-08}	5.15×10^{-04}	2.43×10^{-03}	1.62×10^{-03}		2.67×10^{-03}
	lag			*1*	*4*		*4*
Personal Consumption		0.91***	3.80***	0.16***		-22.27***	0.07***
	Std.Error	1.19×10^{-08}	2.13×10^{-04}	2.97×10^{-03}		3.44×10^{-03}	7.67×10^{-04}
	lag			*1*		*0*	*4*

Note: The parameters are estimated after removing the insignificant variables from prior multivariate estimations. Unreported estimation results reveal that GDP, SET and FX variables are insignificant in any portfolio. *** Significant at 1%, ** Significant at 5%, * Significant at 10%

TABLE 8

Time Series Correlation between Principal Components and Economic Variables

Principal Components	GDP	SET	UMP	MPI	FX	INF	RIR
1st Component	-0.13	-0.20	-0.72	-0.30	0.04	0.64	0.15
2nd Component	0.08	-0.06	0.28	0.21	0.01	-0.53	0.04
3rd Component	-0.09	0.15	-0.19	-0.11	-0.04	-0.31	0.03
4th Component	-0.08	0.04	-0.08	-0.02	-0.18	-0.13	-0.10
5th Component	0.07	0.22	0.04	-0.08	0.16	-0.03	0.16

Note: The symbols GDP, SET, FX, and MPI represent the change versus 1 year ago in the logarithm of the value. The data cover the period from the 3rd quarter of 2001 to 4th quarter of 2014. The percentages of the total variance explained by each component are as follows: 65.92% for the first component, 27.73% for the second component, 3.78% for the third component, 1.47% for the fourth component, and 1.09% for the fifth component.

Figure 1 shows the portfolio exposure (υ_{kj}) to each principal component. Table 10 reports the value of exposure. The result suggests that the five portfolios are highly concentrated towards the first principal risk component with positive exposure in all portfolios. The exposure of the portfolios to this principal component seems to be offset by the exposure to the interest rate since the first principal risk component and interest rate are positively correlated. This is because the positive exposure of the portfolio to the first principal component determines the positive relationship between the wealth of the portfolio and this first principal component as represented by (4) and (8). In addition, the positive exposure of the portfolio to the interest rate factor determines the positive relationship between the level of debt obligation and this factor as represented by (2) and (3). The factor loadings of unemployment and MPI of all the portfolios are positive, while they are negative for inflation; however, the correlation between MPI and the first principal component, and unemployment and the first principal component are negative, and between inflation and the first principal component is positive. It can be seen that the first principal risk component increases the risk to portfolio loss in the same direction as generated by unemployment, MPI, and inflation. Therefore, high exposure to the first principal risk component is regarded as a major source of concentration risk faced by the industrial loan portfolios.

TABLE 9

Time Series Correlation between Latent Factors and Economic Variables

Latent Factor	GDP	SET	UMP	MPI	FX	INF	RIR
$Y_{Agriculture}$	-0.15	-0.11	-0.69	-0.34	-0.02	0.79	0.06
$Y_{Manufacturing}$	-0.11	-0.03	-0.67	-0.37	0.08	0.76	0.14
$Y_{Commerce}$	-0.14	-0.16	-0.73	-0.35	0.03	0.83	0.10
$Y_{Real\ Estate}$	-0.13	0.11	-0.38	-0.19	-0.07	-0.11	0.03
$Y_{Personal\ Consumption}$	-0.07	-0.20	-0.50	-0.16	0.05	0.31	0.16

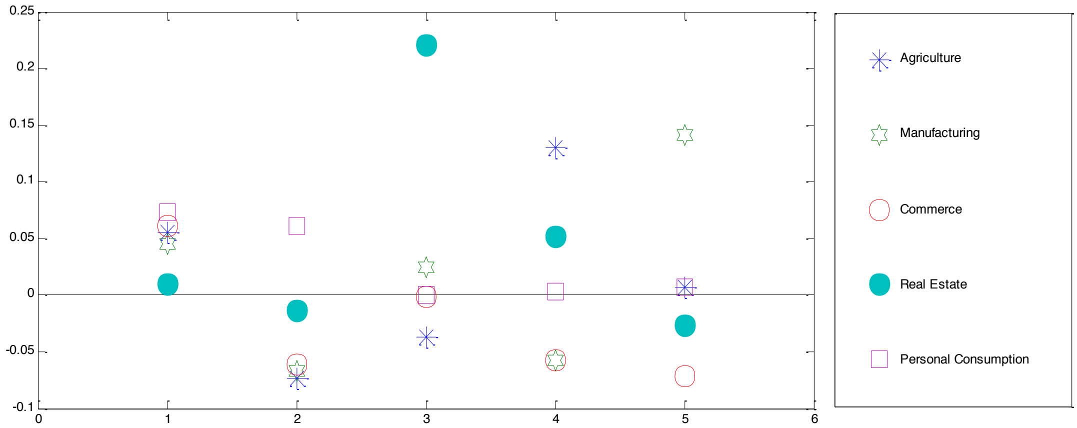


FIGURE 1

Portfolio Exposure to Each Principal Component

Note: All portfolios positively expose to the first principal component with the highest in personal consumption portfolio.

TABLE 10

Exposure of Industry Loan Portfolio to Principal components

Industry	1st Component	2nd Component	3rd Component	4th Component	5th Component
Agriculture	0.06	-0.07	-0.04	0.13	0.01
Manufacturing	0.04	-0.07	0.02	-0.06	0.14
Commerce	0.06	-0.06	0.00	-0.06	-0.07
Real Estate	0.01	-0.01	0.22	0.05	-0.03
Personal Consumption	0.07	0.06	0.00	0.00	0.01

The Empirical Analysis

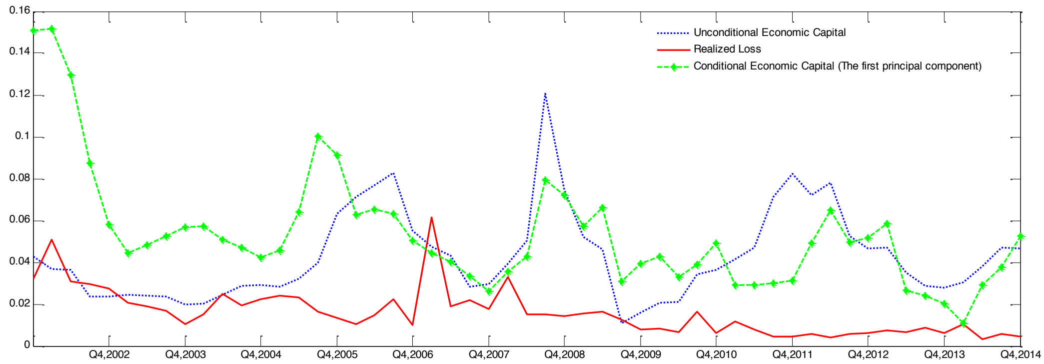
I start this part of the paper by introducing the definition of risk capital.

Definition A: *Unconditional Capital at Risk at the q confidence level is the amount of capital, namely unconditional economic capital (EC), required to absorb the loss of a loan portfolio over a target horizon T within a given confidence level q. The q-unconditional capital at risk or q-unconditional economic capital of portfolio j is measured by equation (12) using the loss and economic data of the current period to estimate the unconditional EC of the next period.*

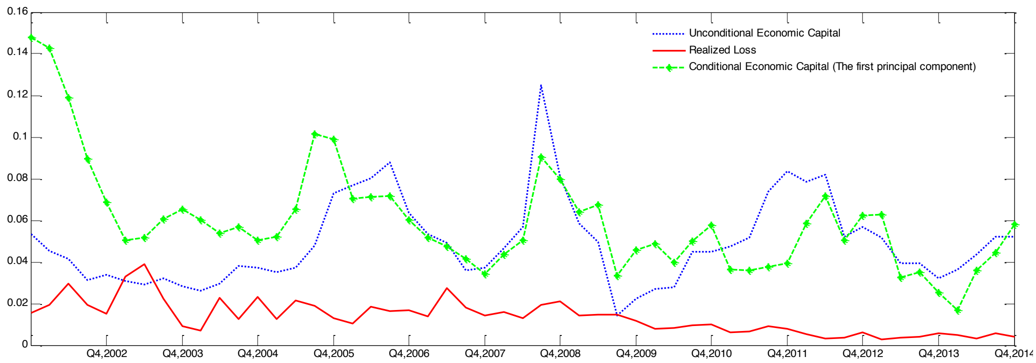
Definition B: *K^{th} Component Conditional Capital at Risk at the q confidence level is the amount of capital, namely the K^{th} component conditional economic capital (EC), required to absorb the loss of a loan portfolio over a target horizon T within a given confidence level q considering a specific distress event of the realization of the K^{th} principal component. The q-conditional on the K^{th} component capital at risk or economic capital of portfolio j is measured by equation (16) using the loss and economic data of the current period to estimate the unconditional EC of the next period.*

Employing conditional risk capital as a loss cushion may be more effective than using the unconditional capital. Figure 2 shows the estimated risk capitals of the portfolio loss quantile at 99.99% according to (12) for the unconditional capital requirement, namely unconditional EC, and (16) of the first principal component compared for the conditional EC against the realized loss. The estimated economic capital of each quarter takes the loss and economic data from the current period to be the capital to absorb the loss of the next quarter. The realized loss is the loss of the current period and the EC is estimated using the loss and economic data from the previous quarter. The capital requirement measured in Figure 2 is time varying throughout the economic cycle. The number of periods in which the realized loss breaches the unconditional portfolio EC is as follows: 6 for agriculture, 3 for manufacturing, 3 for commerce, 0 for real estate, and 15 for personal consumption. Conditional portfolio EC of each quarter is estimated from (16) using the data of the previous quarter which is the capital to absorb loss at 99.99% loss quantile under each economic regime considering the event of the most prominent risk to occur (conditional on the first principal component). The number of periods the realized loss breaches the conditional portfolio EC are as follows: agriculture 1 period, manufacturing 0, commerce 0, real estate 0, and personal consumption 8. Therefore, this suggests that conditional EC safeguards against a portfolio shortfall during high risk better than the unconditional EC does. Conversely, the conditional EC is less conservative during tranquil periods. For example, as shown in Figure 2 the unconditional EC of the personal consumption portfolio during period from Q4-2013 to Q4-2014 (the periods of low realized loss) demands a higher amount of capital than the conditional EC.

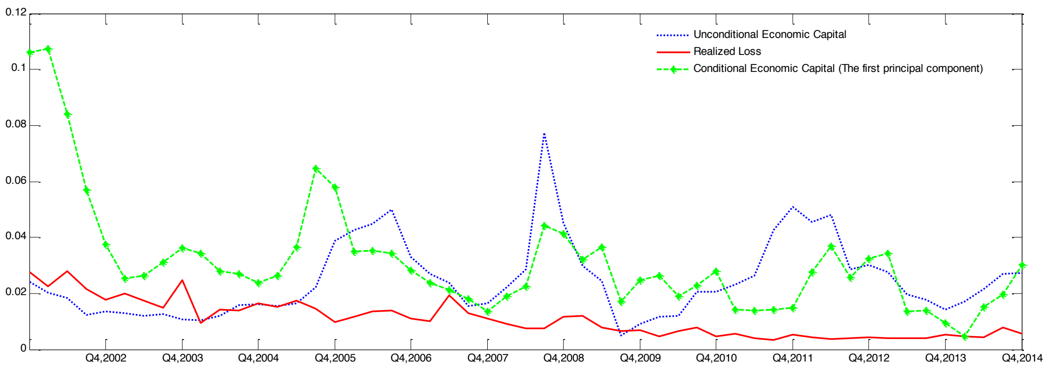
The previous section unveils that the first principal component is the source of concentration risk of industry portfolios because all the portfolios have the positive exposure to this component and it correlates with many economic variables, which are inflation, MPI and unemployment, in the direction that contributes to the default risk. However, this principal component correlates with the interest rate in the opposite direction that contributes to the default risk. In addition, the diversification due to other principal components should reduce the event of simultaneous extreme losses of these industry portfolios. Therefore, the test to examine whether the first principal component is a major source of risk that creates simultaneous large default loss of these industry portfolios is performed as follows.



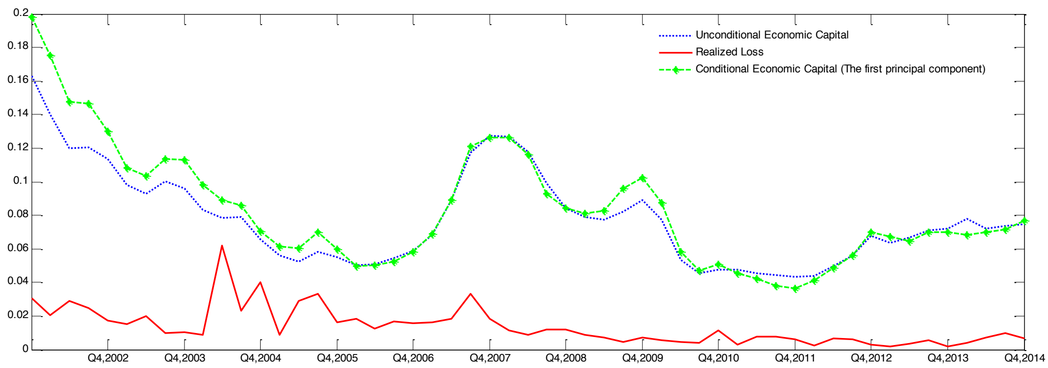
Agriculture



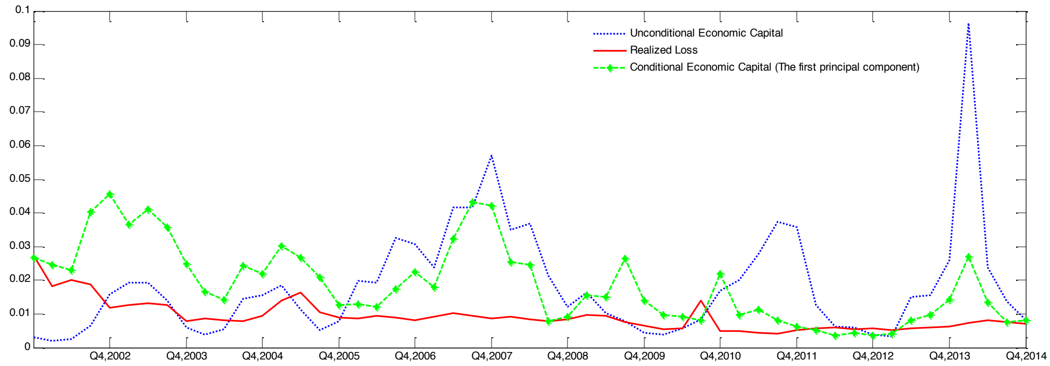
Manufacturing



Commerce



Real Estate



Personal Consumption

FIGURE 2

Portfolio Economic Capital (EC) and Realized Loss

Note: Unconditional portfolio EC is estimated from (12) using the data of the current quarter, which is the capital to absorb loss at 99.99% loss quantile under each economic regime to be the capital for absorbing loss of the next quarter. The realized loss is the loss of the current period and the EC is estimated using the loss and economic data from the previous quarter. The number of periods in which the realised loss breaches the unconditional portfolio EC is as follows: agriculture 6 periods, manufacturing 3, commerce 13, real estate 0, and personal consumption 15. Conditional portfolio EC of each quarter is estimated from (16) using the data of the previous quarter which is the capital to absorb loss at 99.99% loss quantile under each economic regime considering the event of the most prominent risk to occur (conditional on the first principal component).

I conduct the test whether the extreme loss event, the event that the amount of loss exceeds the specified quantile $\tilde{q}$ of the loss distribution conditional on the economic regime, can be determined by the excess capital demanded by each principal risk factor (the conditional economic capital measured by (16) over the unconditional economic capital measured by (12)).

TABLE 11

The Principal Component as a Predictive Variable to Excess Default Rate: $\tilde{q}$ = 0.5

Principal Component	Industry	Agriculture	Manufacturing	Commerce	Real Estate	Personal Consumption
1st PC	$\hat{b}_0$	0.14	-0.51**	0.35*	0.41**	0.68***
	$\hat{b}_1$	37.75***	42.12***	49.22***	45.5*	65.25***
2nd PC	$\hat{b}_0$	0.64***	-0.02	0.63***	0.59***	0.84***
	$\hat{b}_1$	42.09***	25.47***	45.19**	-28.07	60.7***
3rd PC	$\hat{b}_0$	0.38**	-0.08	0.41**	1.64***	0.58***
	$\hat{b}_1$	41.71	93.47	-515.33	17.51**	13456.24**
4th PC	$\hat{b}_0$	1.16***	0.02	0.78**	0.57***	0.51***
	$\hat{b}_1$	55.83**	28.05	96.73	1.02	270.54
5th PC	$\hat{b}_0$	0.34*	0.74	0.68**	0.57***	0.87***
	$\hat{b}_1$	237.81	38.96*	64.56	-23.55	3300.04**

Note: The first principal component as a predictive variable to predict one quarter ahead the excess default rate, the realized loss exceeding the loss at the 50th quantile of the conditional loss distribution $L_{\tilde{q}j}|x$ at $\tilde{q}$ equal to 0.5, which is measured by the realized loss over the mode of loss distribution of the same period. *** Significant at 1%, ** Significant at 5%, * Significant at 10%.

The analysis results from qualitative response models following the probit binomial are reported in Tables 11-14, demonstrating that the first principal risk factor contributes significantly to the event of extreme loss. The probit model of each portfolio takes the following form:

$$P\left[l_{jt} > L_{\tilde{q},j}|x_t\right] = \Phi\left(\hat{b}_{0k} + \hat{b}_k\left(\overline{L_{qjk}}|x_{t-1} - L_{qj}|x_{t-1}\right)\right), \tag{19}$$

where $\overline{L_{qjk}}$ is the capital conditional on the k^{th} principal component, $\widehat{Y_k}$, and $\hat{b}_{0k}$ and $\hat{b}_k$ are the parameter-pair to be estimated. In addition, $\overline{L_{qjk}}|x_{t-1}$ and $L_{qj}|\, x_{t-1}$ are defined in (12) and (16) at q = 0.9999.

The analysis is carried out for the loss threshold $\tilde{q}$ at 0.5, 0.8, 0.9 and 0.999. The results show that only the first principal component explains the loss exceeding the median and 80th quantile of the loss distribution conditional on the economic regime of any five industry portfolios. In addition, only the first principal component explains the loss beyond the 99th quantile of agriculture, manufacturing, commerce and personal consumption. Since all these four industries have positive exposure to the first principal component and the real estate has very low exposure which is 0.01, the first principal component is a risk factor that drives simultaneous loss at the high quantile of agriculture, manufacturing, commerce and personal consumption but not the real estate. We can conclude that the first principal component explains the large default loss in four out of five industrial portfolios and these portfolios are subject to concentration risk exposure. If the state of the economy turns to affect the first principal risk factor adversely, the four portfolios are at risk of simultaneous default leading to a large loss, which can reach at the 99.9th quantile of loss distribution. Also note that the third principal component drives the loss above the 90th quantile of the real estate portfolio, because it has the high exposure to the third principal component. Therefore, the large loss in the real estate portfolio happens at a different regime from those driving the large loss in other industries.

TABLE 12

The Principal Component as a Predictive Variable to Excess Default Rate: q̃ = 0.8

Principal Component	Industry	Agriculture	Manufacturing	Commerce	Real Estate	Personal Consumption
1st PC	$\hat{b}_0$	-0.19	-0.95***	0.13	-0.53**	0.46*
	$\hat{b}_1$	33.1***	47.47***	80.66***	41.82**	123.31***
2nd PC	$\hat{b}_0$	0.29	-0.31*	0.55***	-0.31*	0.63***
	$\hat{b}_1$	38.14***	14.51*	67.71***	-22.88	87.91***
3rd PC	$\hat{b}_0$	0.11	-0.34*	0.26	0.51	0.29
	$\hat{b}_1$	30.55	75.03	-365.36	14.65**	7125.14
4th PC	$\hat{b}_0$	0.94**	-0.06	0.89***	-0.29*	0.29
	$\hat{b}_1$	58.61**	63.33	169.84**	26.57	-861.45
5th PC	$\hat{b}_0$	0.06	0.84	0.65**	-0.29	0.53**
	$\hat{b}_1$	-145.36	55.71**	97.01*	106.24	2947.1**

TABLE 13

The Principal Component as a Predictive Variable to Excess Default Rate: $\tilde{q}$ = 0.9

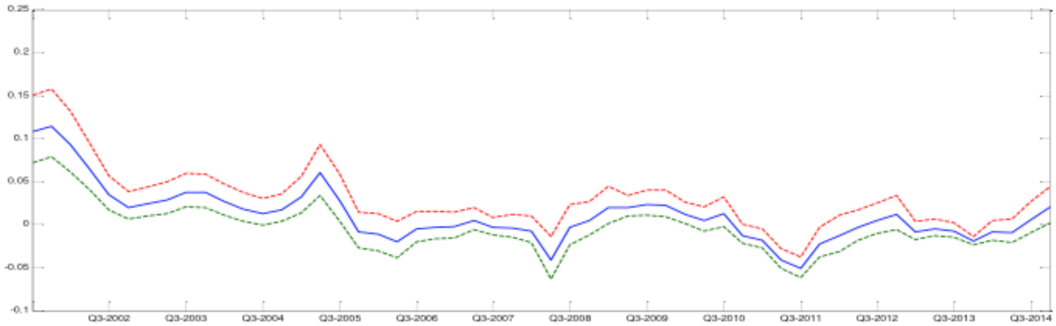
Principal Component	Industry	Agriculture	Manufacturing	Commerce	Real Estate	Personal Consumption
1st PC	$\hat{b}_0$	-0.45**	-1.2***	-0.07	-0.61***	0.33
	$\hat{b}_1$	40.84***	47.71***	43.28***	-3.96	109.84***
2nd PC	$\hat{b}_0$	0.12	-0.47**	0.39*	-0.64***	0.54**
	$\hat{b}_1$	39.69***	14.71*	70.59***	12.57	79.52***
3rd PC	$\hat{b}_0$	-0.02	-0.51***	0.12	1.37**	0.23
	$\hat{b}_1$	40.68	16.83	-201.52	40.21***	5896.96
4th PC	$\hat{b}_0$	1.24***	-0.22	0.75**	-0.63***	0.24
	$\hat{b}_1$	91.76***	62.71	174.91**	-0.2	-879.42
5th PC	$\hat{b}_0$	-0.09	0.93*	0.49*	-0.62***	0.47**
	$\hat{b}_1$	-159.51	69.01***	96.2*	78.31	2823.47**

TABLE 14

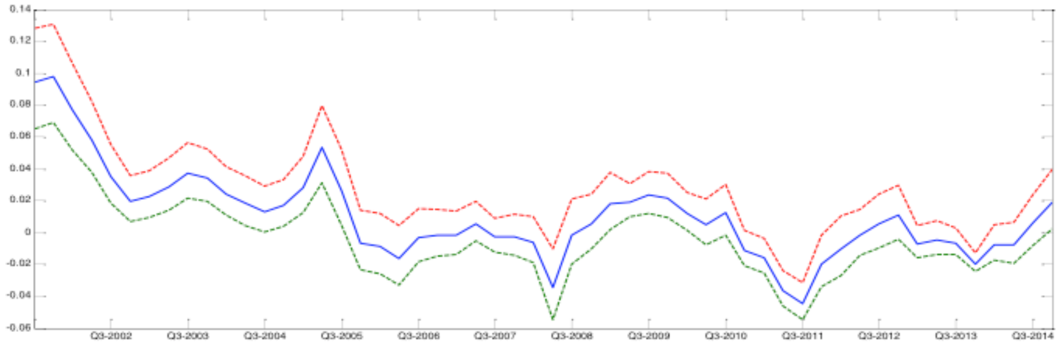
The Principal Component as a Predictive Variable to Excess Default Rate: $\tilde{q}$ = 0.999

Principal Component	Industry	Agriculture	Manufacturing	Commerce	Real Estate	Personal Consumption
1st PC	$\hat{b}_0$	-1.27***	-1.87***	-0.8***	-1.86***	-0.35
	$\hat{b}_1$	34.86***	24.24***	28.77***	12.79	150.25***
2nd PC	$\hat{b}_0$	-0.64***	-1.29***	-0.42**	-1.83***	0
	$\hat{b}_1$	11.49	6.82	51.51**	-39.75	29.76
3rd PC	$\hat{b}_0$	-0.65***	-1.33***	-0.52***	-1.09	-0.11
	$\hat{b}_1$	30.32	91.14	1985.87	14.22	4931.19
4th PC	$\hat{b}_0$	-0.23	-1.35***	-0.05	-1.78***	-0.1
	$\hat{b}_1$	33.7	-7.68	142.07*	23.86	-990.77
5th PC	$\hat{b}_0$	-0.72***	-1.2*	0.09	-1.79***	-0.02
	$\hat{b}_1$	-286.05	5.39	184.3**	75.75	1149.1

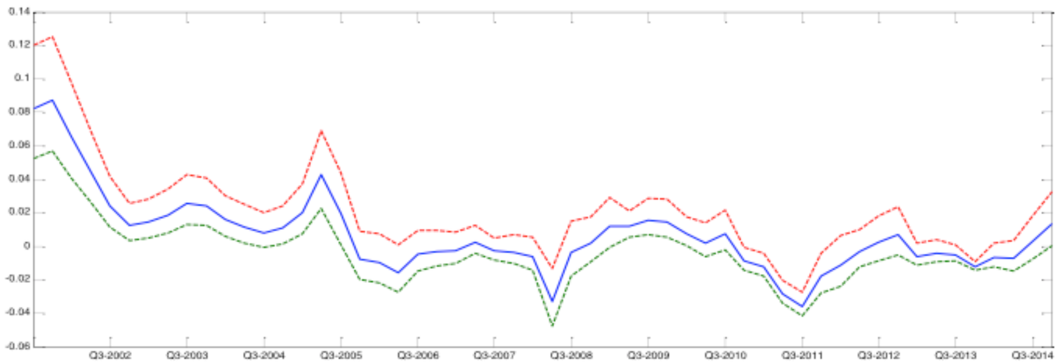
This concentration risk effect suggests that portfolio managers assess the aggregate EC of the total portfolio in addition to the EC of each industrial portfolio for capital planning to avoid breaching the limit of the total portfolio EC, because the risk factor concentration may lead to the violation of the subadditivity axiom of the coherent risk measure (Artzner, Delbaen, Eber, & Heath, 1999). That the EC of the aggregate portfolio may exceed the sum of the industry portfolio EC has been mentioned in a number of studies (Acerbi & Tasche, 2002; Lim, Shanthikumarb, & Vahn, 2011). Figure 3 shows the sensitivity of the extra EC, the conditional EC in excess of the unconditional one, to the change in the first principal component. Since the risk factor is normally distributed by construction, the three standard deviation of the principal component risk factor covers the realization up to the 99.9 percentile. Considering the filtered principal component and the set of economic variables realized in the same period, I sensitize the principal component for three standard deviations from the filtered value and evaluate the amount of conditional EC in excess of the unconditional one. As expected, the extra amount of capital of the real estate portfolio is less sensitive to the variation of the first principal component as the range of excess capital is less volatile (with range standard deviation of 0.0028) compared to those of other portfolios.



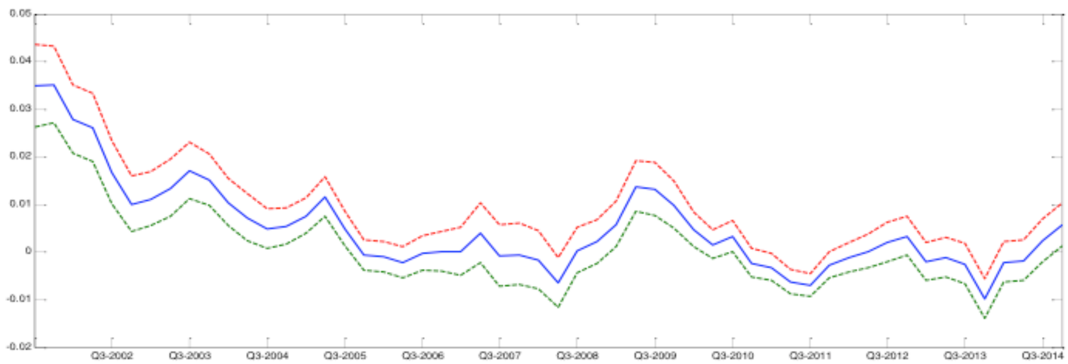
Agriculture



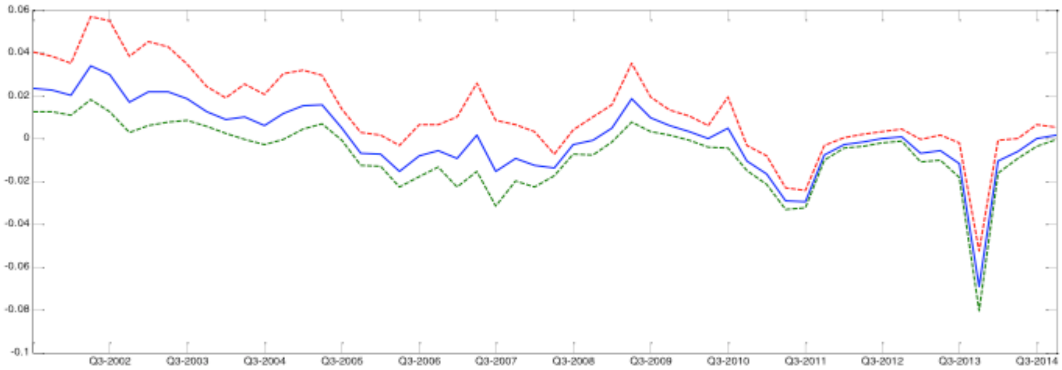
Manufacturing



Commerce



Real Estate



Personal Consumption

FIGURE 3

Factor Sensitivity of EC to the Change in the First Principal Risk Component

Note: The standard deviation of the range of the excess capital of each portfolio is as follows: 0.0139 for agriculture, 0.0102 for manufacturing, 0.0126 for commerce, 0.0028 for real estate, and 0.0105 for personal consumption.

CONCLUSION

I examined the degree of risk factor concentration at the industry level of the aggregated country loan portfolio using Thailand's data. A portfolio without any single name concentration such as the retail loan portfolio may expose to the same risk factor as other industrial loan portfolios. The result shows that the conditional capital on which the risk factor that all portfolios concentrate, can better safeguard against the capital shortfall due to a large extreme default loss comparing to the unconditional one. Moreover, the conditional capital is less conservative during the good economic regime, which enables banks to free up capital resources to lend more during good periods. I show that the risk capital concentration can drive a large portfolio loss simultaneously. The higher the level of concentration, the more likely that multiple portfolios will exhibit a large default loss simultaneously during the distress period. This provides an important insight for regulators to evaluate an extra amount of capital cushion needed to mandate banks to hold in anticipation of an economic downturn when the risk of loss is most likely. Importantly, because the capital concentration has increasingly gained attention after the recent 2008 global financial crisis, this research finding supports the capital concentration aspect of an internal capital adequacy assessment criteria according to pillar 2 of the New Basel Accord, which is adopted widely by banking regulators in most nations. Because concentration risk affects portfolio EC numerously by economic regimes, the credit pricing should consider concentration risk especially for the long maturity loan. Therefore, this paper points the direction of future research on the concentration risk effect in credit pricing of long maturity loans taking into account the investment of an optimal loan portfolio, which is a central unsolved issue to both risk management and strategic credit portfolio management.

APPENDIX

Appendix A

The proof of (10)

I denote $P\left[L_{ij}=1\middle|Y_j,x_T\right]$ by $p(Y_j|x_T)$ and follow the proof in Vasicek (1991). The conditional cumulative probability that the percentage loss on a portfolio does not exceed is l given by:

$$\bar{\bar{F}}\left(l;c_j,\rho_j,\beta_j,\widehat{K}_j\middle|x_T\right)=\sum_{i=1}^{[l\widehat{K}_j]}\binom{\widehat{K}_j}{i}\int_0^1 p\left(Y_j\middle|x_T\right)^i\left(1-p\left(Y_j\middle|x_T\right)\right)^{K_j-i}dP\left[p\left(Y_j\middle|x_T\right)\right]\ , \tag{A.1}$$

where $[l\widehat{K}_j]$ is the nearest integer of $l\widehat{K}_j$.

By the law of large numbers, when $\widehat{K}_j$ is large, the binomial probability mass function of number of defaults with parameters $\widehat{K}_j$ and $p\left(Y_j\middle|x_T\right)$ converges to a normal distribution with a mean of $\widehat{K}_j p\left(Y_j\middle|x_T\right)$. This implies that the j^{th} portfolio loss converges to its expectation $p\left(Y_j\middle|x_T\right)$ in the limit. In consistence with Vasicek's work (2002), the cumulative distribution of $p\left(Y_j\middle|x_T\right)$ denoted by $P\left[p\left(Y_j\middle|x_T\right)\right]$ can be represented by:

$$P[L\ \le l]=P\left[p\left(Y_j\middle|x_T\right)\ \le l\right]=P\left[\Phi\left(\frac{\Phi^{-1}\left(c_j\right)+\beta_j{}'x-Y_j\sqrt{\rho_j}}{\sqrt{1-\ \rho_j}}\ \right)\le l\right] \tag{A.2}$$

$$P[L\ \le l]=P\left[\frac{\Phi^{-1}\left(c_j\right)+\beta_j{}'x-\Phi^{-1}(l)\sqrt{1-\rho_j}}{\sqrt{\rho_j}}\le Y_j\right] \tag{A.3}$$

$$P[L\ \le l]=\ P\left[p\left(Y_j\middle|x_T\right)\ \le l\right]=\ \ \Phi\left(\frac{\sqrt{1-\rho_j}\Phi^{-1}(l)-\Phi^{-1}\left(c_j\right)-\beta_j{}'x}{\sqrt{\rho_j}}\right) \tag{A.4}$$

When $\widehat{K}_j$ is infinitely large and l is significantly greater than zero, it is satisfied by:

$$\lim_{K_j\to\infty}\sum_{i=1}^{[l\widehat{K}_j]}\binom{\widehat{K}_j}{i}\ p\left(Y_j\middle|x_T\right)^i\left(1-p\left(Y_j\middle|x_T\right)\right)^{\widehat{K}_j-i}=1\ \ . \tag{A.5}$$

Therefore, a large loan portfolio cumulative loss distribution function (A.1) is given by:

$$\begin{aligned}\lim_{K_j\to\infty}\bar{\bar{F}}\left(l;c_j,\rho_j,\beta_j,K_j\ \middle|x_T\right)&=\ F\left(l;c_j,\rho_j,\beta_j\middle|x_T\right)\\&=\Phi\left(\frac{\sqrt{1-\rho_j}\Phi^{-1}(l)-\Phi^{-1}\left(c_j\right)-\beta_j{}'x}{\sqrt{\rho_j}}\right).\end{aligned} \tag{A.6}$$

The proof of (11)

By definition, I obtain:

$$f\left(l;c_j,\rho_j,\beta_j\middle|x\right)=\ \frac{dF\left(l;c_j,\rho_j,\beta_j\middle|x_T\right)}{dl}=\frac{dF\left(l;c_j,\rho_j,\beta_j\middle|x_T\right)}{d\Phi^{-1}(l)}*\frac{d\Phi^{-1}(l)}{dl}. \tag{A.7}$$

It is clear that:

$$\frac{dF\left(l;c_j,\rho_j,\beta_j\middle|x_T\right)}{d\Phi^{-1}(l)}=\ \sqrt{\frac{1-\rho_j}{\rho_j}}\,\phi\left(l;c_j,\rho_j,\beta_j\middle|x_T\right), \tag{A.8}$$

where ϕ is the standard normal density function, and the derivative of its inverse can be given by:

$$\phi\left(l; c_j, \rho_j, \beta_j | x_T\right) = \phi\left(\frac{\sqrt{1-\rho_j}\Phi^{-1}(l) - \Phi^{-1}\left(c_j\right) - \beta_j{}'x}{\sqrt{\rho_j}}\right). \tag{A.9}$$

$$\frac{d\Phi^{-1}(l)}{dl} = \frac{1}{\frac{dl}{d\Phi^{-1}(l)}} \tag{A.10}$$

Since $l = \Phi(\Phi^{-1}(l))$, l can be written as:

$$l = \int_{-\infty}^{\Phi^{-1}(l)} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz \tag{A.11}$$

$$\frac{dl}{d\Phi^{-1}(l)} = \frac{1}{\sqrt{2\pi}} e^{-\frac{[\Phi^{-1}(l)]^2}{2}}. \tag{A.12}$$

By plugging (A.10) – (A.12) into (A.7), I obtain (11).

The proof of (12)

By replacing l with L_q in (10), I obtain:

$$F\left(L_q; c_j, \rho_j, \beta_j | x\right) = \Phi\left(\frac{\sqrt{1-\rho_j}\Phi^{-1}\left(L_q\right) - \Phi^{-1}\left(c_j\right) - \beta_j{}'x}{\sqrt{\rho_j}}\right) = q \ . \tag{A.13}$$

By taking an inverse of $F^{-1}(q; c_j, \rho_j | x)$, I obtain:

$$L_{qj} | x = \Phi\left(\frac{\sqrt{\rho_j}\Phi^{-1}(q) + \Phi^{-1}\left(c_j\right) + \beta_j{}'x}{\sqrt{1-\rho_j}}\right) = F\left(q; 1-c_j, 1-\rho_j, -\beta_j | x\right) , \tag{A.14}$$

which is given by (12). Q.E.D.

Appendix B

From (15)

$$\bar{F}\left(L_q; c_j, \sqrt{1-\rho_j}, \| V_{kj} \|, \upsilon_{kj}, \beta_j, \middle| \widehat{Y_k}, x\right) = \Phi\left(\frac{\sqrt{1-\rho_j}\Phi^{-1}\left(L_q\right) - \Phi^{-1}\left(c_j\right) - \beta_j' x + \upsilon_{kj}\widehat{Y_k}}{\| V_{kj} \|}\right) = q \tag{B.1}$$

$$\overline{L_{qjk}} | \, x = \Phi\left(\frac{\| V_{kj} \| \, \Phi^{-1}(q) + \Phi^{-1}\left(c_j\right) + \beta_j' x - \upsilon_{kj}\widehat{Y_k}}{\sqrt{1-\rho_j}}\right) = \bar{F}\left(q; 1-c_j, \| V_{kj} \|, \sqrt{1-\rho_j}, -\upsilon_{kj}, -\beta_j \middle| \widehat{Y_k}, x\right) \tag{B.2}$$

Q.E.D.

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