ORIGINAL RESEARCH:

Vietnamese banks' decision making in lending to small & medium enterprises (SMEs) based on soft and hard information

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Abstract

This study explores the use of soft and hard information for bank lending decisions to small and medium enterprises (SMEs) in Vietnam. Using a unique dataset based on a survey conducted in Ho Chi Minh City, Vietnam, we investigated to what extent different types of information were used for loan approval, whether the two types of information were used in a complementary manner, and what factors determined the banks' lending decisions. The analytical methods used include descriptive statistics for overall assessment, principal component analysis and confirmatory factor analysis to establish and test the scales, and logistic regression to examine determinants of lending decisions. Research results indicate that although collateral-based lending was the most widespread method and could substitute for other lending technologies, usually a combination of lending information types were utilized in the decision making process. This suggests that both complementarity and substitutability were found in the use of the various information types by Vietnamese banks for such decision making.

Keywords: Hard and soft information, lending technologies, loan approval process, small and medium enterprises (SMEs), Vietnam.

Introduction

A considerable amount of literature has been published on the important role of bank loans to SMEs in developed economies (Blackwell and Winters, 2000; Aristeidis and Dimitris, 2005; Rao, 2010). The literature has also acknowledged the obstacles banks confront in lending to SMEs. These obstacles include a severe information asymmetry between SMEs and banks (Frame et al., 2001), high failure rates of SMEs (Levin and Travis, 1987), and the complex combination of the SME representatives' personal and their companies' financial situation (Hannan and Freeman, 1984). In order to alleviate these issues, bank loan officers must find a different approach and techniques to SMEs as compared with larger enterprise customers. These consist of requiring sufficient collateral, requiring audited financial statements and credit scoring, as well as building long-term relationships with SMEs.

Adequate collateral and long-term relationships between lenders and borrowers are believed to help lessen the issue of information asymmetry (Frame et al., 2001; Binks and Ennew, 1997). Additionally, a solid interrelationship between banks and borrowers create trust which mitigates the problem of moral hazard. Petersen and Rajan (1994) insist that a close relationship with the bank enhances credit flow to SMEs and diminishes the interest rate offered for firms. Depending on the business environments as well as the competition in the credit market, banks pursue and develop their own lending technologies. Berger and Udell's (2006) define lending technology as "a unique combination of primary information sources".

The two main lending technologies used to finance SMEs include transaction-based lending which is based on borrowers' hard information, and relationship lending which is principally based on borrowers' soft information. Hard information is quantitative, easy to store, evaluate and transmit, and its content is

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independent of the collection process while soft information is essentially qualitative in nature, and so cannot be easily recorded in written form. Stein (2002) identified hard information as any information that is effortlessly confirmable (e.g. financial statement, payment history records) while soft information cannot be straightforwardly certified by anyone except for the agent who provides it (e.g. management skills, plans and strategy).

Regarding the role of hard and soft information, there has been no consistent agreement among scholars about whether hard and soft information are complementary or substitutive in lending activities. Mason and Stark (2004) claim that loan officers tend to emphasize on the firm's past financial records rather than information on human capital or development strategies of the firm. Similarly, Bruns and Fletcher (2008) acknowledge that the borrower's previous profitability ratio is the most significant factor, and the borrower's financial position is the second most important factor. Less imperative factors include the firm's proficiency in the business project and the firm's collateral pledgeability. In other words, the above studies emphasize more on the role of hard information or transaction technologies than that of soft information. On contrary, a number of studies analyze the importance of soft information, especially for SME financing. For example, according to Agarwal and Hauswald (2007), soft information considerably influences both credit availability and interest rates offered to SMEs. Grunert et al. (2005) observe that soft information represents an imperative component in assessing the default risk of SMEs borrowers.

Berger and Udell (2006) suggest that lending technologies are not necessarily discriminative. Commercial lenders may combine different lending technologies in loan approval process though one key lending technology may be emphasized. Similarly, Uchida et al. (2006), by creating four lending technologies indices (real estate lending, other fixed-asset lending, financial statement based lending and relationship lending), conclude that diverse lending technologies are highly complementary, although financial statement based lending technology may be the most regularly used. On the other hand, Chang et al. (2006) find that hard information and soft information act as substitutes. They suggest that while large banks emphasize on quantitative information, small banks focus more on qualitative information.

In sum, hard information is conventionally considered suitable for comparatively large and transparent corporations while soft information is viewed as best-suited for small and opaque SMEs (Diamond, 1991; Petersen, 2004). However, recent studies in this field have had a different viewpoint. For example, Berger and Udell (2006) disagree with the conventional view by arguing that most of the transaction-based lending technologies or some types of hard information can be employed to lend to opaque SMEs. However, this alternative has not been examined practically.

When making loan decisions based on relationship, scholar often focus on quantitative indicators such as the duration of the bank-firm relationship, the number of bank products the firm is using, and the number of lending relationships (Petersen and Rajan, 1994; Ongena and Smith, 2000). Thus relationship lending is assumed to be primarily based on the relationship between the bank and its existing customers. However, in practice, for potential borrowers or non-regular customers which apply for loans, loan officers also consider soft information such as the entrepreneur's management skills and integrity. Therefore, it is a serious shortcoming if we do not consider soft information when examining the types of information used for loan approval process especially in developing countries like Vietnam. In such countries, banks confront greater uncertainties and struggle to deal with collecting reliable information, stemming in part from the underdeveloped business environment and the low level of regulatory oversight (Nguyen et al., 2006). Therefore, our study contributes to the literature of lending technologies by including new measures of soft and hard information, namely the credit history information and information on firms' social capital.

This study is also different from several previous researches in computing composite indices of information types or lending technologies, because instead of using a simple average method (Uchida et al., 2006; Bartoli et al., 2013), we used a variety of attributes obtained from experienced loan officers and bank managers and used factor analysis to achieve good scales of the information types used for loan approval. Thus we were able to construct information indices considering the level of importance of each attribute for the corresponding factor.

Although previous studies have investigated the lending technologies from the standpoint of SMEs in developed countries (Uchida et al., 2006; Francesca et al., 2013), our study attempts to address the issue of information types influencing on lending decisions from the perspective of the lender side. We believe this is a good approach to explore the bank lending technologies and corresponding information types used for loan approval process since it examines the choice of lending technologies from the standpoint of those who make the loan decision.

To the best of our knowledge, in developing countries, particularly in Vietnam, there is almost no study investigating how and which lending technologies or information types are used in lending to the SMEs. This inspired us to do an empirical research to shed a light on interactions among sources of soft and hard information and their impact on lending decisions in Vietnam.

Methodology

A survey method would be more suitable for identifying and evaluating less quantitative explanatory variables and thus we used it as the major method to collect data. Other methods and analysis techniques were also used such as descriptive method, expert consultations and econometric analysis based on Likert-scale values.

A preliminary phase of qualitative research was carried out to identify the principal attributes influencing small business lending decisions by commercial banks. The attributes were then further supplemented by unstructured interviews with two managers of Credit Committee at Asia Commercial Bank and Sai Gon Commercial Joint Stock Bank, respectively and six loan officers at SMEs Credit Department of commercial bank branches including Asia Commercial Bank, Sacombank, Vietcombank, An Binh Bank, Techcombank, Sai Gon Commercial Bank, located in Ho Chi Minh city, Vietnam.

Based on the findings of this phase, a set of 52 attributes was established as potentially influencing on bank lending decisions. This set was divided into 7 main categories: (i) business organization, (ii) the entrepreneur's financial information, (iii) collateral eligibility, (iv) the entrepreneur/owner's capability and integrity, (v) firm networks, (vi) relationship lending, (vii) credit history record on the firm and its owner.

Participants in the survey: The target respondents of the survey were loan officers working at Credit Departments for SMEs at commercial banks, including state-owned banks and joint stock banks. In order to achieve the highest response rate in a limited time and cost, we employed a convenient sampling method. We utilized our available networks in Vietnam banking system to distribute the questionnaire to approximately 250 loan officers at credit departments of commercial bank branches in Ho Chi Minh City where most of Vietnam commercial banks' head offices are located.

Ho Chi Minh City is also the most dynamic city in the financial - economic arena with the highest density of bank branches and SMEs. The survey was carried out from May 2013 to September 2013. A total number of 218 replies were collected, achieving a response rate of 86%.

Data analysis technique: After the data was coded, examined and cleaned, the following data analysis techniques were employed in this order: reliability test of scales with Cronbanch's alpha indicator, explanatory factor analysis (EFA), confirmatory factor analysis (CFA) with testing for validity and reliability of the model, and finally logistic analysis. The statistical parameters of each step were compared with the criteria applied in the analysis of multivariate data (Nunnally, 1978; Hair et al., 2010).

EFA was used to group and define major factors which affect lending decisions to SMEs. One of the topics the researchers discuss around factor analysis issues is the number of factors being retained, which is the most vital judgment to make after extracting factors. A misstep at this stage, such as extracting too many or two few factors, may cause incorrect conclusions in the analysis (Fabrigar et al., 1999; Hayton et al., 2004).

In deciding how many factors should be retained, researchers are often advised to consider several criteria: a predetermined number of factors based on research objectives and/or prior research, the percentage of variance criterion (Hair et al., 2010); Kaiser's eigenvalue-greater-than-one rule; scree plot (Hair et al., 2010) and Horn's parallel analysis (PA). Among these, PA is the most recommended method to deal with the number of factors-to-retain issue, though it is not available in commonly used statistical packages (Humphreys and Montanelli, 1975; Zwick and Velicer, 1986). Generally, the principal criteria for factor analysis were set as follows:

Kaiser-Meyer-Olkin (KMO): from 0.50 to 1.00;
Number of factors to retain was decided according to the result of PA;
Significant level: less than 0.01;
The cumulative percentage of variance: 60.0 % or higher

The results from EFA and CFA were then used in binary logistic regression to examine the impact of each of the factors that may influence SMEs lending decisions as well as to find out the most influential factors. The logit model was formed as follows:

Logit (ρ) = Log [$\rho i/(1-\rho i)$] = $\beta 0 + \beta 1F1 + \beta 2F2 + \beta 3F3 + \ldots + \beta nFn$, of which:
ρ i = the probability of loan application being accepted;
β 0= log odds of firms whose loan application are rejected (when all Fi = 0)
β i= log odds of firms whose loan application are approved (when Fi = 1)

Findings and Results

Attributes influencing lending decisions to SMEs:
The responses to questions about attributes influencing lending decisions to SME were structured using the 5 point Likert scale. The scale for each attribute ranged from 'very unimportant' (1) to 'very important' (5). Table 1 shows the perception of loan officers on attributes influencing their lending decisions to SMEs.

The firm's collateral eligibility was the most important attribute in bank lending decisions to SMEs with the highest mean. The next important factors influencing bank lending decisions were attributes related to information on credit history and financial performance of firms. Other relatively important factors included attributes related to social capital variables such as the entrepreneur's capability, integrity or trust and the firm's networking.

Table 1: Descriptive statistics of attributes influencing lending decisions

Attributes	Mean	Std. Deviation
A1_Firm Size	3.59	0.777
A2_Corporate brand name	3.10	0.836
A3_Information about resources of firm	3.85	0.744
A4_Management philosophy & system	3.34	0.783
A5_Promising businesses	3.82	0.837
A6_Business schedules	4.04	0.701
A7_Information on Customers, market, supplier	3.67	0.672
A8_Clear and professional accounting system and reports	4.18	0.625
A9_Sales and profit	4.41	0.625
A10_Assets & Capital Sources	4.20	0.669
A11_Liquidity Ratio	4.06	0.686
A12_Capital structure Ratios	4.17	0.665
A13_Profitability Ratios	4.27	0.714
A14_Operating Ratios	4.07	0.768
A15_Cash Flow Statement	3.74	0.808
A16_Personal assets of the SME's representative	4.50	0.537
A17_Pledgeability of real estate collateral	**4.66**	**0.512**
A18_Pledgeability of tangible assets collateral	**4.68**	**0.506**
A19_The entrepreneur has relevant background and education	3.08	0.886
A20_Experience in the field of business	3.48	0.51
A21_Experience in management	3.44	0.516
A22_Strategic Planning Ability	3.29	0.486
A23_Uses IT in managing business	2.65	0.773
A24_Good at selecting the needed resources	3.44	0.525
A25_Good at understanding market evolution	3.26	0.608
A26_Makes positive impression with bankers	3.26	0.768
A27_Shows positive learning in working with bank	3.22	0.704
A28_Positive referral on integrity	2.94	0.826
A29_Willingness to share sensitive and real information	2.97	0.839
A30_Positive experience with working with banks	3.06	0.735
A31_Adapts interests with those of commercial partners	2.86	0.707
A32_Pays attention to the needs of employees	1.99	0.826
A33_Honest during negotiations with commercial partners	3.09	0.673
A34_Consistent in behavior and decisions	3.25	0.641
A35_Strong personal network with banks	3.21	0.659
A36_Strong personal network with government officials	2.97	0.675
A37_Strong network with the entrepreneurs at other firms	3.11	0.642
A38_Relationship with customers	3.11	0.66
A39_Relationship with suppliers	2.96	0.691
A40_The length of the bank-entrepreneur relationship	3.64	0.499
A41_The entrepreneur has been borrowing your bank	4.02	0.595
A42_The entrepreneur has been borrowing other banks	4.27	0.624
A43_Your bank is main bank	3.68	0.515
A44_Number of your bank products the firm is using	2.85	0.584
A45_Positive credit information in transactions with banks	4.30	0.566
A46_Type and value of collateral securing the loan in the past	4.36	0.51
A47_Negative credit information in transactions with banks	4.62	0.548
A48_Bankruptcies of owner	4.28	0.705
A49_Ppersonal financial information on the owners	3.92	0.701
A50_ Utility payment records	3.23	0.816
A51_Court judgments	3.94	0.706
A52_Credit enquiries from other lenders	4.12	0.618

The results show that hard information still plays a critical role in loan approval process of Vietnam commercial banks. Soft information is also utilized in loan application assessment but it just plays a supplementary role in this procedure. In contrast to our expectation and some studies in the literature which have shown that banks use soft information more than hard information in dealing with SMEs lending, Vietnam commercial banks make hard information a priority in SMEs loan approval process.

Testing the reliability of scale:

The reliability statistics shown in Table 2 indicated that the Cronbach's alpha of all facets reached a good level (above 0.7), while the 'business organization' facet was still acceptable (0.685). However, the Corrected Item-Total Correlation coefficients of attribute A1, A7, A10, A19, A26, A44 and A50 were low (<= 0.3), indicating that the corresponding item does not correlate very well with the overall scale and, therefore, it may be eliminated (Field A., 2005). The removal of those attributes would result in a higher Cronbach's alpha. Therefore, the attributes A1, A7, A10, A19, A26, A44 and A50 were removed in turn to ensure the highest reliability of scales.

Explanatory factor analysis (EFA):

Although common statistical packages do not offer parallel analysis (PA), we utilized the SPSS syntax created by O'Connor (2000) to run PA. According to PA results, only seven factors should be retained (Table 3).

Next, we carried out principal component analysis with seven factors extracted. Only attributes or facets which had communality value and significant factor loadings would be retained. The satisfactory communality value and significant factor loadings that may guarantee convergent validity for the analysis were 0.4 and 0.6 (or higher), respectively. Accordingly, there 10 attributes were removed alternately from the model after principal factor analysis (PCA) had been applied at the very first step, including: A2, A3, A51, A4, A5, A32, A29, A6, A15 and A46. The final PCA result is displayed in Table 4.

The results of the final analysis showed the KMO value of 0.806 which indicated a high appropriateness for the use of the principal component analysis. Furthermore, the value of Bartlett's test of sphericity at a statically significant level indicated the strength of the relationship among variables.

The results of the rotated component matrix are shown in Table 4. We can see that there are few changes in the categorization of important attributes affecting bank lending decisions. The attribute of 'Firm's outstanding loan at other banks' (A42) is associated with 'Credit History Information' despite being included in the 'Bank Relationship' category. However, in terms of empirical meaning, the recombination is still acceptable.

As the explanation of each factor is based on the variables having large loadings, seven factors were identified as follows: (1) financial Information, (2) integrity of the entrepreneur, (3) capability of the entrepreneur, (4) credit history Information, (5) information on the firm's network, (6) bank relationship of the firm, (7) collateral eligibility.

With respect to validity and reliability, the analysis satisfied the requirement of convergent validity, discriminant validity, face validity and the consistency of the item-level errors within a single factor (reliability). First, convergent validity is evident by the factor loadings. With a sample size of approximately 200, sufficient factor loadings should be at least 0.50 (Hair et al., 2010).

Table 2: Reliability statistics of Cronbach's alpha test

	Scale Mean if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
Business Organization - Alpha = 0.685			
A1	***21.92***	***0.166***	***0.709***
A2	22.44	0.484	0.623
A3	21.7	0.467	0.630
A4	22.21	0.484	0.624
A5	21.71	0.453	0.633
A6	21.5	0.469	0.632
A7	*21.88*	*0.241*	*0.687*
Financial Information - Alpha = 0.88			
A8	28.65	0.581	0.871
A9	28.47	0.633	0.866
A10	***28.62***	***0.309***	***0.899***
A11	28.77	0.669	0.863
A12	28.75	0.652	0.864
A13	28.69	0.709	0.858
A14	28.9	0.714	0.858
A15	29.08	0.596	0.871
Collateral Eligibility - Alpha = 0.725			
A16	8.64	0.526	0.662
A17	8.51	0.586	0.587
A18	8.69	0.529	0.657
The entrepreneur's Capability - Alpha = 0.75			
A19	**24.76**	***0.313***	***0.763***
A20	24.17	0.493	0.717
A21	24.13	0.548	0.711
A22	24.24	0.596	0.701
A23	24.62	0.455	0.723
A24	24.32	0.598	0.699
A25	24.21	0.548	0.708
A26	**24.6**	***0.235***	***0.77***
The entrepreneur's Integrity - Alpha = 0.802			
A27	20.36	0.533	0.778
A28	20.68	0.559	0.773
A29	20.65	0.392	0.801
A30	20.53	0.576	0.771
A31	20.75	0.542	0.776
A32	21.47	0.413	0.799
A33	20.5	0.616	0.767
A34	20.33	0.545	0.778
The entrepreneur 's Network - Alpha = 0.866			
A35	12.14	0.58	0.864
A36	12.38	0.658	0.846
A37	12.26	0.809	0.808
A38	12.25	0.763	0.820
A39	12.41	0.644	0.850
Relationship Lending - Alpha = 0.77			
A40	14.8	0.579	0.718
A41	14.4	0.567	0.718
A42	14.13	0.438	0.763
A43	14.9	0.608	0.705
A44	***15.31***	***0.289***	***0.783***
Credit History - Alpha = 0.817			
A45	27.9	0.566	0.793
A46	28.09	0.434	0.809
A47	27.66	0.584	0.791
A48	27.94	0.668	0.777
A49	28.3	0.703	0.771
A50	**29.13**	***0.304***	***0.830***
A51	28.46	0.512	0.804
A52	28.14	0.583	0.790

Table 3: Parallel analysis results

	Raw data Eigenvalues	Means	Percentile random data Eigenvalues
1	8.3405	2.0346	2.1457
2	4.7796	1.9195	1.9969
3	3.3108	1.8338	1.9013
4	3.1132	1.7591	1.8182
5	2.5119	1.6978	1.7570
6	2.2240	1.6378	1.6923
7	1.8547	1.5844	1.6353
8	1.3334	1.5325	1.5789
…	…	…	…
45	0.1476	0.3791	0.4073

Table 4 shows that factor loadings on every factor were above 0.6, indicating a good convergent validity. Second, examining the rotated component matrix, all variables loaded significantly with only one factor. In other words, there was no issue of cross-loadings. Therefore, the analysis met the requirement of discriminant validity. Third, regarding face validity, it is easy to label the components since variables are generally similar in nature by loading together on the same factor. Finally, in respect of reliability, the Cronbach's alpha for each component or factor was above 0.7, revealing that the analysis was reliable.

Confirmatory factor analysis:

After PCA was used to develop scales, we moved on to CFA. Figure 1 describes the model specification and the parameter estimates. It is apparent from the model that the seven factors of lending decisions correlated with each other. The results of the CFA also indicated that the seven–factor model showed a good fit with acceptable fit indices. All coefficients are significant at $p<0.01$, comparative fit index (CFI)=0.91, root mean square error approximation (RMSEA) =0.054, adjusted goodness of fit index (AGFI)=0.80, standardized root mean square residual (SRMR) < 0.08, and the minimum fit function Chi–Square ratio degrees of freedom (CMIN/DF) =1.63

Figure 1 shows the factor loadings of the CFA. We followed the measure set by Hair et al. (2010) who suggested that factor loading should be 0.5 or higher. The minimum factor loading of our CFA model was 0.57, thus indicating that the independent variables identified a priori represented by a particular factor.

As for validity and reliability when doing a CFA, a few useful measures cab be used including 'composite reliability' (CR), 'average variance extracted' (AVE), 'maximum shared variance' (MSV), and 'average shared variance' (ASV). The measures of validity and reliability are presented in the Table 5.

To evaluate the suitability of those measures, we followed the thresholds sugessted by Hair et al. (2010), as shown in Table 6.

Except for the AVE value of the 'Integrity' factor, the CR, AVE, MSV, ASV measures of of all factors met the requirement for composite reliability, convergent validity and discriminant validity. However, since the 'Integrity' AVE was not far from the suggested threshold of AVE (0.478 and 0.5, respectively), we decided to retain this factor in the model.

Table 4: Final PCA results

	Component						
	1	2	3	4	5	6	7
Cronbach's Alpha	0.876	0.849	0.844	0.849	0.868	0.809	0.763
Eigenvalues	6.885	4.083	3.102	2.835	2.350	1.746	1.576
Cumulative variance explained (%)	11.065	21.592	31.842	41.843	51.508	58.288	64.507
A12	0.782						
A13	0.778						
A14	0.771						
A9	0.736						
A11	0.699						
A8	0.693						
A33		0.799					
A30		0.775					
A34		0.729					
A28		0.725					
A31		0.719					
A27		0.689					
A20			0.812				
A21			0.802				
A24			0.766				
A22			0.723				
A25			0.685				
A23			0.679				
A48				0.805			
A47				0.779			
A45				0.765			
A52				0.688			
A49				0.654			
A42				0.615			
A37					0.873		
A38					0.836		
A39					0.775		
A35					0.731		
A36					0.719		
A40						0.845	
A43						0.833	
A41						0.754	
A17							0.839
A18							0.783
A16							0.771

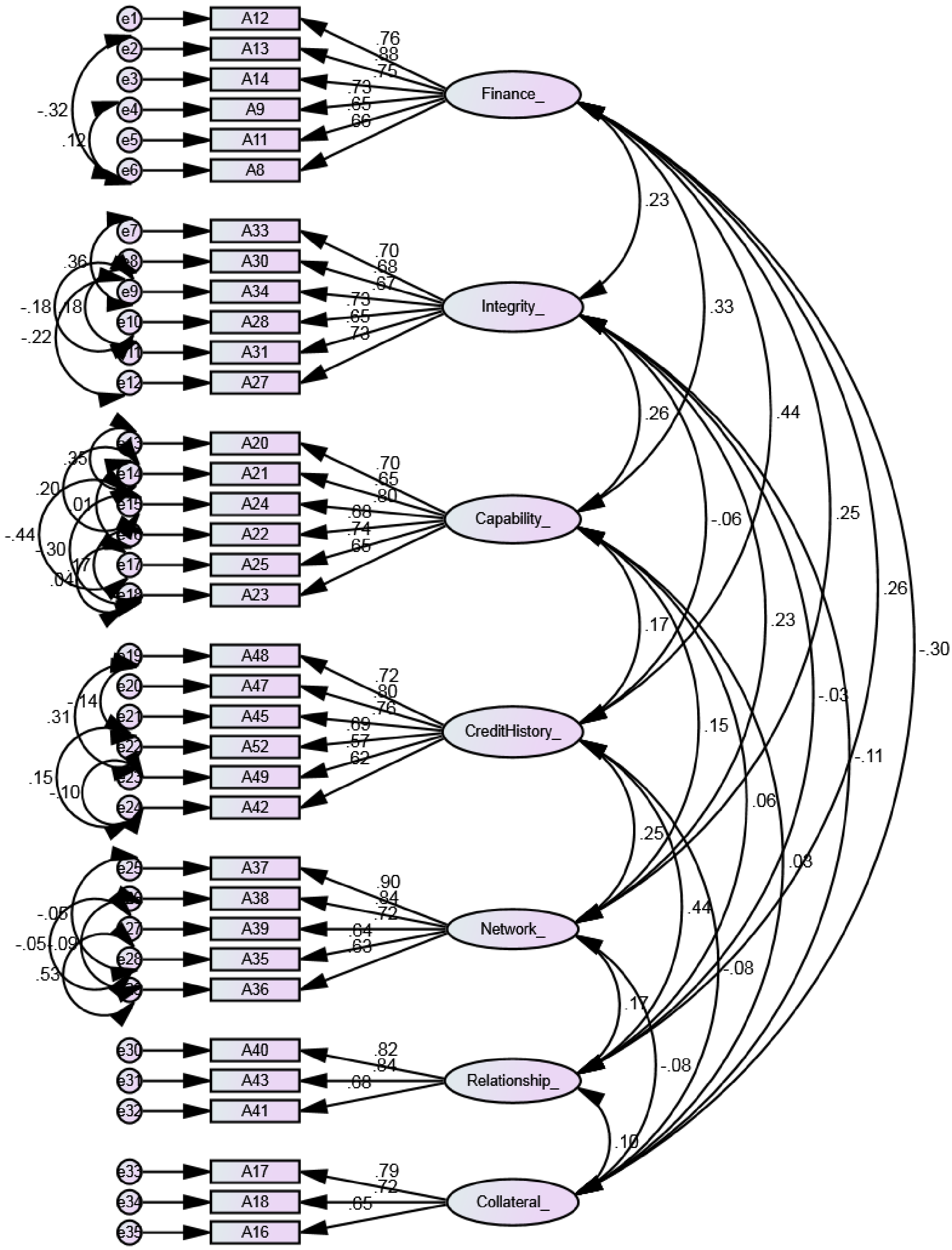

Figure 1: Standardized coefficients (factor loadings) for the seven-factor model

Table 5: Measures of validity and reliability in the data

	CR	AVE	MSV	ASV
Relationship	0.780	0.542	0.238	0.066
Finance	0.882	0.557	0.134	0.081
CreditHistory	0.858	0.548	0.238	0.073
Integrity	0.815	*0.478*	0.100	0.039
Capability	0.835	0.583	0.100	0.030
Network	0.871	0.632	0.066	0.039
Collateral	0.816	0.598	0.088	0.018

Table 6: Thresholds to evaluate reliability and validity (Source: Hair et al., 2010)

	Composite reliability	Convergent validity	Discriminant validity
Thresholds	Factor loading > 0.5 AVE > 0.5; CR > 0.7	CR > AVE AVE > 0.5	MSV < AVE ASV < AVE

In sum, CFA results confirmed that the seven-factor model with 35 attributes was a good measurement model. Therefore, factors extracted from the model can be used to estimate the importance of information facets in bank loan approval process.

Discussion

The relative importance of individual information indices:

We constructed composite scores or indices to represent to what extent loan applications were approved based on the aggregate combination of hard and soft information. The indices were constructed by utilizing the factor analysis's results in the previous part, in which factor loadings were used to compute weights of attributes or items. Factor loadings indicate how strongly the attribute influences the measured variable. The individual weight of each attribute was calculated as the square values of each factor loading divided by the sum of the squared values of the factor loadings of all the attributes (Barrios and Schaechter, 2009). The information indices which represent their important level in loan approval process are shown in Table 7.

It appeared that 'Collateral' with the highest mean (4.59) played the most important role in loan approval process. This suggests that collateral lending is the most widespread lending technology used in Vietnam banks. Along with collateral, information on credit history of the firm ('CreditHistory') and financial performance ('Finance') also influenced substantially on bank lending decisions to SMEs.

It is noteworthy that these three important information indices all belong to the 'hard information' category. In other words, regardless of the fact that soft information also played a certain role in bank lending decisions (the mean values of soft information indices were above 3.0), the loan approval process in Vietnam bank system was mainly based on hard information. The descriptive statistics had already shown the relative importance of individual information indices but still the possibility existed that these information types may not be severely dissimilar from each other and, as a consequence, some complementarity might exist among them. Thus, the analysis of interrelationships among information types was examined in the next step.

Table 7: Descriptive Statistics of information indices used in loan approval process

	Minimum	Maximum	Mean	Std. Deviation
Collateral	3.00	5.00	4.5939	0.44966
CreditHistory	3.00	5.00	4.2988	0.47473
Finance	2.98	5.00	4.1957	0.54069
Relation	2.29	4.65	3.7311	0.47549
Capability	2.24	4.14	3.2840	0.42925
Network	1.56	4.19	3.0868	0.52217
Integrity	1.84	4.00	3.0547	0.53512

Complementarity among the information indices:

Before proceeding with the analysis of the complementarity among information types, we combined the three factors of ‘capability’, ‘integrity’ and ‘network’ into one, for the following reasons. First, theoretically, the literature review on social capital suggests that trust (capability and integrity included) and networks are the most important components. Second, in order to ease the problem of multi-colinearity and to have the ideal sample size for multivariate regression in the following stage, it was necessary to lessen highly correlated independent variables. Therefore, integrity, capability and network were combined in a composite index, namely ‘SocialCap’. The combination of three soft information indices did not change the important order of information indices.

Far beyond our expectation, some interesting results were obtained as shown in Table 8. First, there was a significant negative correlation between ‘Collateral’ and ‘Finance’, which indicated that these two types of information are not complementary but substitutive. Moreover, the ‘Collateral’ variable showed no association with other information indices at a significant level. It seemed that the collateral based-lending technology was used relatively independently from other lending technologies.

In other words, if a small firm can satisfy the strict requirements of collateral pledgeability by banks, it is highly likely that the bank will accept the firm’s loan application without taking into account the information on financial statements, credit history reports or other information types such as the firm’s relationship with banks, integrity, capability and networks. For banks, sufficient collateral was the highest guarantee for creditworthiness of borrowers. This unexpected result is also different from previous studies on the choice of lending technologies for SMEs that show collateral based lending technology is used in a complementary way with other lending technologies (Uchida et al., 2006; Francesca et al., 2013).

Second, ‘SocialCap’ and ‘Relation’ showed no statistically significant correlation with each other though both are categorized as soft information. It is possible that the firm-bank relationship was measured in a quantitative manner with attributes of ‘hard information’ such as the length of the firm-bank relationships, and number of bank products used by the firm, while social capital’s attributes were mainly constructed from ‘soft information’. There are significant differences between soft and hard information in screening and monitoring processes; therefore, these two types of information may not be used concurrently.

Table 8: Pearson correlation of the five information indices

	Collateral	Finance	CreditHistory	Relation	SocialCap
Collateral	1				
Finance	-0.236** (0.000)	1			
CreditHistory	-0.062 (0.362)	0.415** (0.000)	1		
Relation	0.079 (0.248)	0.243** (0.000)	0.383** (0.000)	1	
SocialCap	-0.052 (0.449)	0.323** (0.000)	0.179** (0.008)	0.076 (0.264)	1

Note: ** Correlation is significant at the 0.01 level (2-tailed).

A highly significant positive correlation existed between other combinations of indices,. Especially, the magnitude of correlation was very high between 'Finance' and 'CreditHistory', between 'CreditHistory' and 'Relation', 'SocialCap' and 'Finance'. This implies that these pairs of information types are highly complementary and frequently used at the same time by loan officers in the loan approval process.

Logistic Regression on Determinants of Lending Decisions:

We examined the level of firm response to important information for lending decisions. In the survey, besides asking loan officers about the importance of each type of information, we also asked them to reminisce a recently specific firm loan application which they were in charge of and then evaluated the level of firm response to the corresponding information for loan approval. The level of firm response was assumed to be represented by the firm's willingness to provide the necessary information for loan approval.

We investigated the impact of the level of firm response to required information on bank lending decisions through a binary logistic regression model. In addition, in order to integrate the importance of attributes with the level of firm response to the corresponding attributes, we used the factor loadings from the previous factor analysis result to construct composite scores of factors that appeared to have an influence on the bank loan approval process. Table 9 displays the statistics of composite scores describing the firm response level to important information.

Table 9: Composite scores of the firm response level to important information

	N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
R-CreditHistory	218	1.12	4.88	3.40	0.91
R-Finance	218	1.31	5.00	3.26	0.78
R-Collateral	218	1.62	5.00	3.17	0.65
R-Capability	218	1.70	4.53	3.08	0.58
R-Network	218	1.00	4.24	2.89	0.66
R-Integrity	218	1.47	4.28	2.84	0.64

Among response indices, 'R-CreditHistory' had the highest mean value (3.40), followed by 'R-Finance' (3.26) and 'R-Collateral' (3.17). These indices are categorized as the firm response level to hard information required for loan approval. It is reasonable that loan officers find it easy to collect and verify hard information, especially information provided by a third party such as credit history reports from credit bureaus. Firms that have a clear and professional reporting system or sufficient fixed assets to pledge as collateral are completely confident to provide reliable hard information required by loan officers.

On the contrary, the level of firm response to soft information such as the entrepreneur's capability, integrity and networks was not very strong. It may be because loan officers have not emphasized on these types of information due to the high costs and the time needed to collect soft information. Since small businesses are often short of management skills and experience in working with banks, they may lack the ability to present themselves strongly in order to create the trust with the bank loan officers.

Logistic Regression on Determinants of Lending Decisions:

The dependent variables and predictors (independent variables) used in the logistic regression are defined and displayed in Table 10.

Table 10: Description of Variables

Code	**Description of Variables**		Variable used in the model
Dependent Variables			
Lending-De	Bank Lending Decision	1-Accept, 0-otherwise	x
Independent Variables			
R-CreditHistory	Firm Response to Credit Information	Ratio scale variable	x
R-Finance	Firm Response to Financial Information	Ratio scale variable	x
R-Collateral	Firm Response to Collateral Information	Ratio scale variable	x
R-Capability	Firm Response to Information on Capability	Ratio scale variable	
R-Integrity	Firm Response to Information on Integrity	Ratio scale variable	
R-Network	Firm Response to Information on Network	Ratio scale variable	
R-SocialCap*	Composite score of R-Capability, R-Integrity, and R-Network	Ratio scale variable	x
Rel-Years**	The length of the bank-firm relationship in years	Ratio scale variable	x
MainBank	The surveyed bank is the firm's main bank	1-Main Bank, 0-otherwise	x
ExBorrower	The firm used to borrow at the surveyed bank	1-Ex–borrower, 0-otherwise	x

Note: *The construct of R-Capability, R-Integrity and R-Network into a composite score, namely R-SocialCap is to meet the requirement of sample size for binary logistic regression.

**The last three variables measure the relationship lending of the firm

Logistic regression Results:

We used forward stepwise logistic regression to explore if the independent variables mentioned in the previous part affected the probability of loan application acceptance. The independent variables included in the model include those that had correlation with the dependent variable according to parametric and/or non-parametric tests results. Table 10 summarizes the logistic regression results at the last step.

The Hosmer-Lemeshow test which gives a measure of the agreement between the observed outcomes and the predicted outcomes showed a high p value ($p = 0.472$), indicating that the model does not adequately fit the data. The model accounted for between 60.0% and 88.3% of the variance in bank acceptance status.

As shown in Table 11, only the firm response to collateral (R-Collateral), the firm response to financial information (R-Finance), the firm response to credit information (R-CreditHistory), and 'Main-bank' factors together reliably predicted bank lending decision. The results also show that the firm response to social capital, the length of bank-firm relationship and ex-borrower status are insignificant determinants of the bank lending decision, though these variables show a significant association with the independent variable in the bivariate analyses.

Table 11: Logistic regression results - Variables in the Equation at the last step

Variables[a]	B	S.E.	Wald	Sig.	Exp(B)
R-Collateral	4.515	1.295	12.167	0.000	91.423
R-Finance	1.728	0.841	4.222	0.040	5.631
R-CreditHistory	2.151	0.776	7.677	0.006	8.596
MainBank	2.26	0.897	6.35	0.012	9.581
Constant	-24.722	5.538	19.931	0.000	0.000
Observations		218			
-2 Log Likelihood		48.509			
R-Squared		0.600 (Cox & Snell)	0.883(Nagelkerke)		

Note: a. Variable(s) tested to enter: R-Collateral, R-Finance, R-CreditHistory, R-SocialCap, Rel-Years, MainBank, ExBorrower

Based on the logistic coefficient (B), the regression model could be written as follows:

$$\textbf{Logit}\ (\rho) = \textbf{Log}\ [\rho_i/(1-\rho_i)] = -24.722 + 4.515^*\ \text{R-Collateral} + 1.728^*\ \text{R-Finance} + 2.151^*\ \text{R-CreditHistory} + 2.260^*\ \text{MainBank}$$

The value of Exp (B) in Table 11 demonstrates how raising a corresponding measure influences the odds ratio. Specifically, the value of the coefficient reveals that an increase of one unit of the firm response to collateral information is associated with an increase in the odds of acceptance by a factor of 91.4. Similarly, for each unit increase in the firm response to financial information and credit information, loan officers were approximately 5.6 and 8.5 times more likely to approve the firm loan application, respectively.

Furthermore, there was strong evidence for the influence of relationship lending factor on lending decisions. At the 95% confidence interval, the firm that applied for a loan to their main bank was approximately 9.5 times more likely to get the loan. Judging from the magnitude of coefficients, it can be said that the firm response to collateral requirement is the most important factor affecting bank lending decisions to SMEs in Vietnam. This finding also coincides with our previous conclusion that collateral-based lending is the most frequently used lending technology, and reflects the collateral principle as the lending practice in Vietnam.

Conclusion

Overall, our analysis provides empirical evidence that hard information such as financial statement, information on collateral and credit history report is superior to soft information in affecting bank lending decisions to SMEs in Vietnam. In particular, the information attributes related to collateral based lending were more frequently emphasized. Furthermore, the findings from logistic regression analysis once again suggest that the firm response to collateral requirement was the most crucial factor which affected bank lending decisions.

There are similarities in the finding of information for lending decision to SMEs between the present study and those described by Uchida et al. (2006) and Francesca et al. (2013). These studies concluded that financial statement lending was the most widespread lending technology. They also insisted that lending technologies were complementary and that multiple lending technologies are often used at the same time. Findings in our study are also consistent with those of the two above empirical studies from the viewpoint that hard information plays a significant role in bank lending decisions and that hard information is connected with soft information to some extent. However, different from those two studies, our study found that collateral based lending was used the most.

To some extent the correlation between collateral information and other information types are not complementary but substitutive. There are several possible explanations for this result. First, this could be explained by the context of bank lending activities in Vietnam where the loan officers' ability of collecting and verifying soft information is limited due to both subjective and objective reasons. Second, the majority of Vietnam SMEs have no audited financial statements and thus loan officers cannot rely upon only financial reports provided by small firms to make lending decisions. Third, regarding credit history information, Vietnam Credit Information Center (CIC) is the only public credit bureau that provides credit reports in which negative information (e.g. information on the firm's bankruptcy, default, and late payment) accounts for a large part of the content. Moreover, CIC's database is incomplete since it has been collecting and disseminating credit information of medium and large companies with the source of information coming from the bank system.

Information from other financial institutions or non-bank institutions (e.g. financial companies, retail companies, utility companies, and courts) is still excluded from this information system. Consequently, regardless of the reliability of credit information reports, loan officers only consider credit information as an important reference source and use it along with other types of information. Fourth, the firms' humble capacity of professional management and inexperience in providing the banks with soft information is one of characteristics of SMEs in general, and Vietnam small business in particular (Nguyen et al., 2006).

Accordingly, from the perspective of lenders, collateral pledgeability is the most transparent, specific and reliable information when they assess a borrower's creditworthiness. The survey used for this study was conducted in the most dynamic city in Vietnam, Ho Chi Minh city, where many large banks and their branches are located. Under the pressure of competition among banks in achieving the target credit growth rate, assessing borrowers' creditworthiness through collecting soft information will lead to costly and time-consuming problems. In this circumstance, relying on hard information is a safer choice.

Leaving hard information aside, the firm-bank relationship is also considered by loan officers in loan approval process. This is to say, relationship lending contributes to some extent to the final lending decision, especially when hard information is insufficient. This finding is in a good match with several empirical studies of relationship lending for the financing of SMEs (Cole, 1998; Angelini et al., 1998).

The findings have some implications for both banks and SMEs. From the bank perspective, they may make a choice among lending technologies and determine the trade-offs in developing their lending strategy, but they can combine several lending technologies at the same time. The competition in the credit market will become fiercer with the participation of not only domestic financial institutions but also foreign players. The currently common practice in lending activities is to use hard information, especially emphasizing on the firm's collateral pledgeability. However, this trend may change in the direction of incorporating more soft information in order to get competitive advantages and become suitable for the majority of SMEs' that are often characterized with having insufficient collateral and unreliable financial information. Bank loan officers should be prepared to work with private businesses under uncertainty and must receive training to collect and verify valuable information through formal and informal networks.

From the entrepreneur perspective, another important implication of these findings is that they must select the bank with a lending strategy that maximizes their probability of obtaining a desired funding source. In addition, conducting a clear and professional reporting system and enhancing the relationship with the main bank will increase the opportunities of accessing bank credit. In the near future, enriching and improving management skills and the ability to provide bank loan officers with soft information need to be considered.

References

Agarwal, S. and Hauswald, R. 2007. The choice between arm's-length and relationship debt: Evidence from eLoans. Working Paper.

Angelini, P., Di Salvo, R. and Ferri, G. 1998. Availability and cost of credit for small businesses: Customer relationships and credit cooperatives. *Journal of Banking and Finance* 22 (8): 925-54.

Aristeidis, G., and Dimitris, F. 2005. Entrepreneurship, small and medium size business markets and European economic integration. *Journal of Policy Modeling* (27): 363 – 374.

Barrios, S. and Schaechter, A. 2009. Gauging by numbers: A first attempt to measure the quality of public finances in the EU. European Economy Economic Paper 382.

Bartoli, F., Ferri, G., Murro, P. and Rotondi, Z. 2013. SME financing and the choice of lending technology in Italy: Complementarity or substitutability*? Journal of Banking and Finance* 37: 5476–5485.

Berger, A. N. and Udell, G.F. 2006. A more complete conceptual framework for SME finance. *Journal of Banking and Finance* 30: 2945-2966.

Binks, M. R. and Ennew, C. T. 1997. Smaller business and relationship banking: The impact of participative behavior. *Entrepreneurship Theory and Practice* 21(4): 83–92.

Blackwell, D. and Winters, D. 2000. Local lending markets: what a small business owner/manager needs to know. *Quarterly Journal of Business and Economics* 39(2): 62–79.

Bruns, V. and Fletcher, M. 2008. Banks' risk assessment of Swedish SMEs. *Venture Capital* 10(2): 171-194.

Chang X., Dasgupta, S. and Hilary, G. 2006. Analyst following and financing decisions. *Journal of Finance* 61: 3009-3048.

Cole, R.A. 1998. The importance of relationships to the availability of credit. *Journal of Banking and Finance* 22: 959-977.

Diamond D., 1991. Monitoring and reputation: The choice between bank loans and directly placed debt. *Journal of Political Economy* 99: 689-721.

Fabrigar, L. R., Wegener, D. T., MacCallum, R. C., and Strahan, E. J. 1999. Evaluating the use of exploratory factor analysis in psychological research. *Psychological Methods* 4(3): 272-299.

Field, A. 2005. Discovering Statistics Using SPSS. 2nd ed. London: Sage.

Frame, S., Srinivasna, A. and Woosley, L. 2001. The effect of credit scoring on small-business lending. *Journal of Money, Credit, and Banking* 33(3): 813–825.

Grunert, J., Norden, L., Weber, M. 2005. The role of non-financial factors in internal credit ratings. *Journal of Banking and Finance* 29: 509-531.

Hair, J., Black, W., Babin, B., and Anderson, R. 2010. Multivariate data analysis (7th ed.): Prentice-Hall, Inc. Upper Saddle River, NJ, USA.

Hannan, M. and Freeman, J. 1984. Structural inertia and organizational change. *American Sociological Review* 49: 149–164.

Hayton, J.C., Allen, D.G. and Scarpello, V. 2004. Factor retention decisions in exploratory factor analysis: A tutorial on parallel analysis. *Organizational Research Methods* 7: 191-205.

Humphreys, L. G. and Montanelli, R. G. 1975. An investigation of the parallel analysis criterion for determining the number of common factors. *Multivariate Behavioral Research* 10: 193-206.

Levin, R. I. and Travis, V. R. 1987. Small company finance: What the books don't say. *Harvard Business Review* 65(6): 30–32.

Mason, Colin and Stark, Matthew. 2004. What do investors look for in a business plan: A comparison of the investment criteria of bankers, venture capitalists and business angels. *International Small Business Journal* 22(3): 227-248.

Nguyen, V. T., Le, N. T. B., and Freeman, N. J. 2006. Trust and uncertainty: A study of bank lending to private SMEs in Vietnam. *Asia Pacific Business Review* 12(4): 547–568.

Nunnally, J.C. 1978. Psychometric Theory, 2nd ed. New York: McGraw-Hill.

O'Connor, B. P. 2000. SPSS and SAS programs for determining the number of components using parallel analysis and Velicer's MAP test. *Behavior Research Methods, Instrumentation, and Computers* 32: 396-402.

Ongena, S., and Smith, D. 2000. What determines the number of bank relationships? Cross country evidence. *Journal of Financial Intermediation* 9: 26-56.

Petersen, M. 2004. Information: Hard and Soft. Working Paper: 1-20.

Petersen, M., and Rajan, R. 1994. The benefits of lending relationships - Evidence from small business data. *Journal of Finance* 49 (1): 3-37.

Aristeidis, G., and Dimitris, F. 2005. Entrepreneurship, small and medium size business markets and European economic integration. *Journal of Policy Modeling* 27: 363 - 374

Stein, Jeremy C. 2002. Information production and capital allocation: Decentralized versus Hierarchical Firms. *Journal of Finance* 57(5): 1891-1921

Uchida, H., Udell, G.F. and Yamori, N. 2006. SME financing and the choice of lending technology. RIETI Discussion Paper Series 06-E-025. Research Institute of Economy, Trade, and Industry.

Zwick, W.R. and Velicer, W.F. 1986. Comparison of five rules for determining the number of components to retain. *Psychological Bulletin* 99: 432-442.