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An Investigation of Primary Bank Index Models

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Abstract

Researchers have demonstrated dramatic increase in profits can come from a small increase in customer retention rate. Especially in financial institutions, many know the 80/20 rule: i.e. that 80 per cent of profits come from 20 per cent of customers. In fact, some banks have found that high profit households may in fact represent in excess of 100 per cent of profits because unprofitable ones subtract so much. Thus, CRM has gained much attention from both the academies and the practitioners, in which it will help managers to focus on a small group of *current* good customers. However, the current good customers might not be the future good customers or the current good customers might have the potential to become even better. In this study, we propose a primary bank index (PBI) for bank industry to indicate customers who treat X Bank as their primary bank. We assumed that customers who treat X Bank as their primary bank have higher propensity to transact with X Bank in the future. Therefore, PBI not only implies the current value of a customer, but also the potential value of a customer. In this study, we propose a PBI predictive model based on CSI model and demographic data. Furthermore, we suggest the future model developments.

Keywords: customer relationship management, customer satisfaction index, CSI, customer potential, data mining.

1. Introduction

In recent years, Customer Relationship Management (CRM) has gained much attention from both the academies and the practitioners. CRM means that companies manage relationships with individual customers with the aid of customer database and interactive and mass customization technologies. Since Reichheld (1993) demonstrated dramatic increase in profits from a small increase in customer retention rate, companies shifted their focus from customer acquisition to retention. These findings indicated that 5 per cent increase in customer retention resulted in an increase in average customer lifetime value of between 35 and 95 per cent, leading to significant improvements in company profitability. Kotler (1992) recognized a shift of paradigm emerging within marketing theory, such as the focus on long-term relationships rather than on short-term exchange transactions. Holmlund and Kock (1996) make this concept clearer that, through long-term relationships with customers, we can get access to detailed and useful knowledge about the customer. Reichheld (1996) concluded that there are six underlying reasons why retained customers are more profitable: (1) Customer acquisition costs may be high, so customers may not become profitable unless they are retained for one or more years, (2) There will be a stream of profits from the customer in each year after acquisition costs are covered, (3) Customers buy more over time, so revenues go up; companies become more efficient at serving them, so costs go down, (4) Retained and satisfied customers may refer other potential customers, and (5) The relationship has a value to the customer too, so that retained customers tend to become less price-sensitive. With the considerable improvements in technology, enterprises can increase their profitability by using analytical techniques to build long-term relationship with customers based on prediction models that draw on a wealth of data about customer behavior. Instead of treating all customers equally, companies must understand that it is more effective to develop customer-specific strategies and target the right customers. By using customer information contained in databases, companies can invest in the customers that are potentially valuable for the company, but also minimize their investments in non-valuable customers. In short, today's marketers should pursue enduring customer relationship instead of just selling products.

Though loyal customers have higher potential for up-selling and cross-selling, there is some special issue for retailing bank service. Customers generally deal with more than one financial institute. A customer may not necessarily spend most with the financial institute in which he or she has the greatest loyalty due to reasons, such as: conveniences or inertia. We propose a primary bank index (PBI), which indicates consumers identify the bank as their primary financial service provider. We assume that customers who treat X Bank as their primary bank have higher propensity to transact with X Bank in the future. This concepts is also similar to the concept of "share of wallet", a predictive index of customers' growth potential with the bank (Zeithaml, 2000).

Therefore, PBI not only implies the current value of a customer, but also the potential value of a customer. Potential value is defined as the profit or value delivered by a customer if this customer behaves ideally, i.e., the customer purchases all products or services he currently buys in the market at full prices at the focal company (Verhoef and Donkers, 2001). There are at least two types of potential customers that draw most of companies' attention. The first type customer: an organization's most profitable customers may only represent ten percent of total customer base or less, but spend 5 to 15 percent more than the average, which has the great potential for up-selling. The second type customer: customers who seem not profitable to the company now but actually have great potential to spend more, which has low current value now but have great potential value.

By using the PBI, we hope to capture these two groups of customers in financial banks.

ACSI (The American Customer Satisfaction Index) is an index to measure the cause-and-effect relationships between satisfaction and loyalty for the United States (Fornell et al., 1996). Reaches have shown CSI can serve as a predictor for companies' profitability (Anderson et al., 1994; Anderson et al., 1997; Eklof et al., 1999) and market value (Ittner and Larcker, 1996; Eklof et al., 1999). In other words, CSI can be further developed as a predicting tool (Anderson and Fornell, 2000). Ittner and Lacker (1996) also estimated that a one-unit change in ACSI is associated with a $654 million increase in the market value of equality above and beyond the accounting-book value of assets and liabilities. Thus, in this study, we propose a CSI model for Taiwan, and since CSI model has been so successful in predicting financial performance, we assumed that customers with higher satisfaction levels towards the bank tend to treat the bank as their primary bank.

Given the above overview, the objective of this study is to develop a framework to predict PBI from CSI. We will compare different modeling techniques, such as: logit regression modeling and artificial neural network, to see which can provide better results for predicting PBI.

By this paper, we extend the CSI and CRM studies in the following aspects. Firstly, a CSI model for Taiwan was proposed, Secondly, a primary bank index (PBI) was proposed and treat it as a proxy of potential contributions of customers, Thirdly, we integrate CSI study with CRM study by using satisfaction scores derived from CSI model to predict the PBI, and finally, a PBI predictive model was proposed for future study.

The organization of this study is as follows. In section 2, we start with literature review and explain the CSI model for Taiwan. In section 3, we describe the methodology and the data requirements for PBI. In section 4, we examine the results of predictive models. Finally, we end with a conclusion, model limitations and directions for future model developments in section 5.

2. Literature review

The first part of this section will be devoted to the construction of CSI model for Taiwan. Next, we will describe the concept of PBI.

2.1. CSI model construction for Taiwan

Based on ACSI (Fornell et al., 1996) and ECSI (Gronholdt et al., 2000; Kristensen et al., 2000; Martensen et al., 2000), we propose an adapted model for X Bank in Taiwan in figure 1. The structural equation model is depicted as follows:

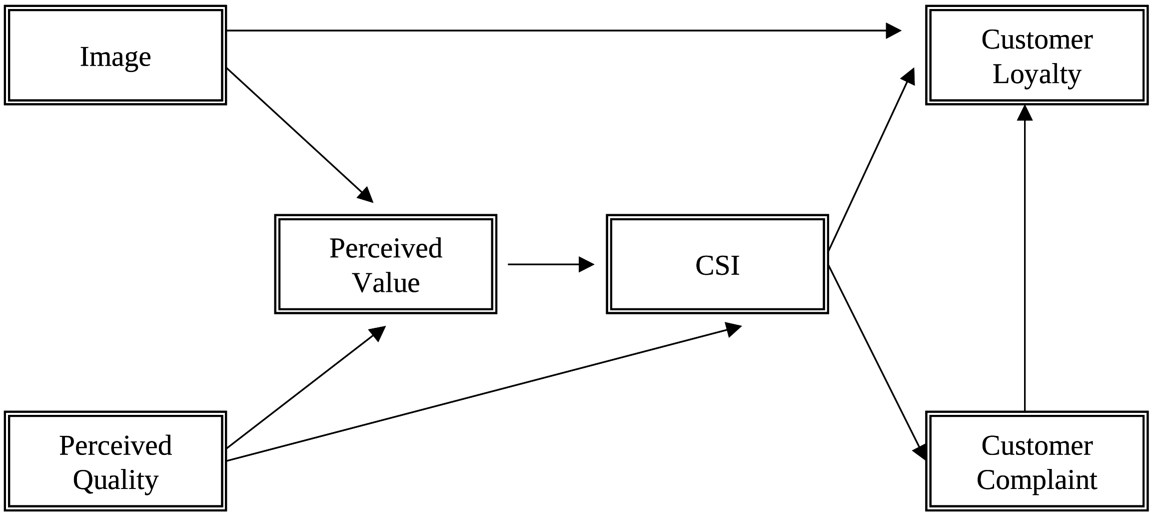

Figure 1. CSI model for Taiwan

The variables on the left-hand side are to be seen as drivers for explaining the Customer Satisfaction Index (CSI) and the right hand performance indicator (loyalty/complaints). Main casual relationships are indicated. A set of manifest (observable or measurable) variables is associated with each of the latent variables. The entire model is important for determining the main goal variable, being CSI.

2.1.1. CSI Antecedents

1. Perceived quality: Perceived quality is different from objective quality (Dodds et al., 1991; Holmlund and Kock, 1996). In customers' viewpoint, it is a global judgment relating to the superiority of the service. We refer to the dimensions of SERVQUAL and modify it according to the characteristics of financial service industry. We explain the dimensions used to measure customers' perceived quality. (1) Reliability: Ability to perform the promised service dependably and accurately, including the service encounters employees' expertise and problem solving ability. (2) Responsiveness: Willingness to help customers and provide prompt service, including conveniences (like service line or ATM) and timely services (like complaint or query handling process). (3) Assurance: Knowledge and courtesy of employees and their ability to inspire trust and confidence. (4) Empathy: Caring, individualized attention the firm provides this customer, including the service encounter employees' attitude, informing relevant information actively, and offering what the customers need continuously. (5) Customization: Whether the bank offering customized service to adapt various individual needs.

2. Company image: Image relates to the brand name and what kind of associations the customers get from the product/brand/company.

3. Perceived value: Perceived value concerns the "value-for-money" aspect as the customer experiences it. It is here seen to be affected by perceived quality as well as image.

2.1.2. CSI consequences

1. Complaints: Complaints relate to the intensity of complaints by the clients and the way the company handles these complaints.

2. Loyalty: Loyalty relates to the repurchase intention and price tolerance (reservation price).

2.1.3. Difference between CSI for Taiwan and ACSI/ECSI

What makes the CSI model for Taiwan different from ACSI model is we do not include the latent variable of customer expectation, and substitute it for company image. There are two reasons that for doing this.

1. Researches have shown that customer expectation doesn't have significant impact on customer satisfaction (Kristensen et al., 2000). Martensen *et al.* (2000) further suggested to remove the customer expectation from ECSI.

2. According to the ECSI empirical study, which found that company image has significant impact on customer loyalty. When customers regard the company has good image, they are more willing to give companies more chances when dissatisfaction situation occurs. On the other hand, company image covers some respect of customer expectation. Thus, we think it is appropriate to substitute customer expectation for company image.

2.1.4. Structural equation model of CSI estimation

As pointed out by Zeithaml (2000), single-item measures have much lower reliability than multiple-item measures. Each latent variable, for example: perceived quality, has many manifest variables to measure it. Several statistical methods can be applied to derive the relationships between the latent variables, such as LISREL, EQS, or PLS. Though CSI studies have also been performed with EQS (Hackl et al., 2000) or with LISREL (Bettencourt, 1997), there is another compelling reason that one might choose PLS over LISREL or EQS. Rather than assume equal weights for all manifest variables in the latent variables, the PLS algorithm allows each manifest variables to vary according to how much it contributes to the score of the latent variables. As a by-product of the design of PLS, the weightings can be used to calculate the score of the latent variable. The score of CSI has implications for managers formulating competitive strategy. One of its key benefits is that ACSI represents a uniform and comparable system of measurement that allows for systematic benchmarking over time and across firms. In addition, it can be useful in analyzing the strengths and weaknesses of the firm of its competitors. Thus, in this study, we used partial least squares (PLS) to drive the relationships of the CSI model.

PLS differs from covariance structure model (CSM) such as LISREL in its basic principles and assumption. In CSM estimation, the probability of the observed data given the hypothesized model is maximized. In PLS estimation, which is a least squares approach, minimizes residual variances. CSM estimators assume a parametric model, a family of joint distributions for all observables; PLS operates as a series of interdependent OLS regressions, presuming no distributional form at all (Fornell and Bookstein, 1982).

2.2. Primary Bank

We propose a primary bank index (PBI), which indicates consumers identify the bank as their primary financial service provider. PBI not only implies the current value of a customer, but also the potential value of a customer. Rust et al. (1995) identify nine key attributes that effect customers' ongoing relationships with their primary bank as follows: (1) The friendliness of the bank? (2) How well the managers know me? (3) How well the bank listens to my needs? (4) How many ATM the bank has around town? (5) How many tellers are available at busy times? (6) The cost of checking? (7) How close is the bank to my home? (8) How close is the bank to my work place? (9) How convenient the bank is to my route to work?

3. Research framework and questionnaire design

This research focuses on constructing a Primary Bank Index Model, which indicates predictive relationships between PBI and CSI. In this section, we first present the framework of our conceptual model. Then we discuss our questionnaire design. Finally, we will describe the proposed Primary Bank Index predictive model in details.

3.1. Conceptual framework

First of all, PBI is not an index can be derived directly from the companies' database. Thus, in the design of CSI questionnaire, we deliberately added one question, "Do you think X bank is your primary bank?" Of course, our final goal is to derive a model to predict PBI not by asking customers, but to use transaction database, demographic data, or satisfaction survey. The ideal conceptual framework for PBI predictive model is depicted in figure 2. However, in this study, we only use demographic data and satisfaction survey to predict PBI. From research in financial service industry, it is well known that the family lifecycle is a determinant of the type services acquired (Antonides and van Raaij, 1998). In addition, Kamakura et al. (1991) reported that demographic factors, such as income, age and education, are important determinants in the acquisition of financial services. On the other hand, we assumed that customers with higher satisfaction levels toward the bank tend to treat the bank as their primary bank.

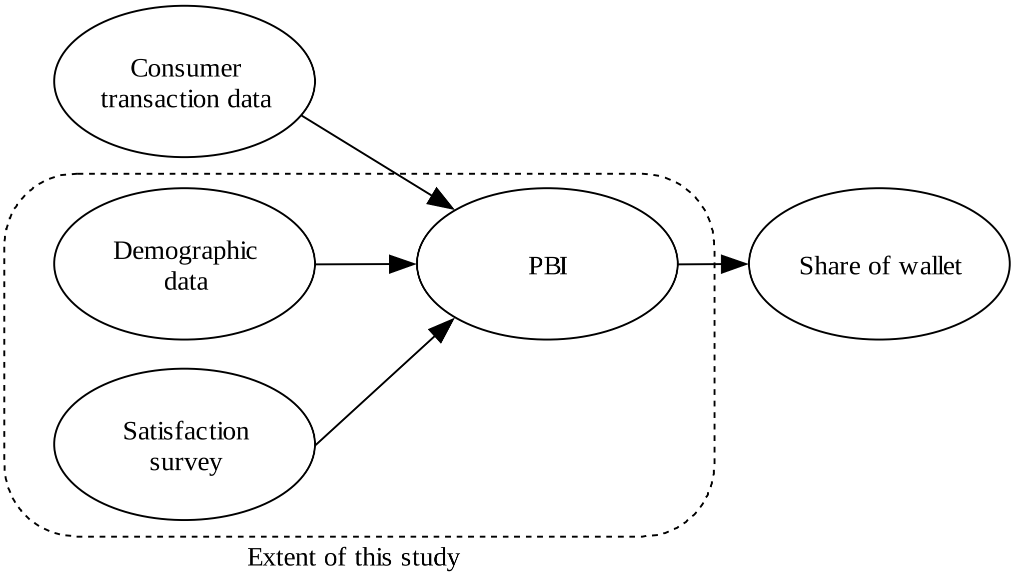

Figure 2. Conceptual framework for PBI predictive model

First, we conducted a CSI survey for X bank. Next, we used *t* test to examine whether there is a difference on the score of customer satisfaction between customers who view X bank as their primary bank (PBI = 1) and those who don't (PBI = 0). The formula of the score of the latent value is:

$$Score = \frac{\sum_{i=1}^{h} w_i \overline{x_i} - \sum_{i=1}^{h} w_i}{9\sum_{i=1}^{h} w_i} \times 100$$

Where h is number of manifests within the latent variable and w_i are the unstandardized weights (Fornell et al., 1996). After making sure the significant difference between these two groups, we will apply data mining techniques – logit regression model vs. artificial neural network – by combing the demographic data and satisfaction index to predict PBI.

3.2. Questionnaire design

We conducted a satisfaction survey for X bank based on CSI model that we proposed on section 2. The survey questionnaire was designed to collect the following information: (1) PBI index, (2) CSI measurement: perceived service quality, company image, perceived value, overall customer satisfaction, customer complaint, customer loyalty, and (3) demographic information: age, marriage, sex, monthly income, residence, and occupation. A more detailed description of the sample characteristics is given in Appendix A. All constructs, except for demographics, were measured on a 10-point scale. For 1 is the lowest and 10 is the highest.

3.3. Primary Bank Index predictive model

The variables used to predict PBI include six demographic variables: age, sex, marriage, monthly income, residence, and occupation, one CSI latent variable. In order to exhibit the effect of CSI, we will present two models. One is a full model, which includes all the variables discussed above, and the other is null model, which only includes demographic variables.

4. Results analysis

In this section, we start with a short description of the survey process and the data. Then we estimated the CSI model and applied it to predict PBI.

4.1. Survey samples and data

Trained interviewers surveyed the selected samples of X bank and conducted telephone interviews. A preliminary survey was done with 30 customers and then we pretested the questionnaire on this small sample and refined the script. The telephone interviews lasted an average of 10~12 minutes. The sample was stratified random sampled from X bank's current consumer-banking customers with only retail banking transaction with X Bank. According to sex, residential area and contribution to X bank, we divided all customers into 20 stratums and then allocated samples to each stratum proportionally. Using this sampling methodology, we obtain a representative sample on these important characteristics. After deleting cases with ambiguous values, we obtained a final sample of 618 customers.

4.2. CSI model results

Before we start to apply CSI to predict PBI, we first check the reliability and validity of the CSI model.

4.2.1. Reliability

Cronbach's α was used to test reliability and the result was presented in table 1. As shown in table 1, except for complaints and loyalty, the value of Cronbach's α were less than 0.7, all the others' Cronbach's α value were greater than 0.8.

Table 1: Cronbach's α of latent variables

Latent variables	Number of measurement variables	Cronbach's α
Perceived quality	10	0.90
Company image	3	0.86

Perceived value	2	0.85
CSI	3	0.87
Complaints	2	0.35
Loyalty	2	0.66

4.2.2. Validity

Validity refers to the ability of the individual measures to represent the underlying construct (CSI) and to relate effects and consequences in an expected manner (Anderson and Fornell, 2000). The validity of the CSI model was checked by R^2 and the statistical significance of the path coefficient. Since customer satisfaction and customer loyalty are the main latent variables used in the CSI model, we only presented their R^2 value in table 2 and the result of path coefficient was presented in table 3.

Table 2: R^2 of two latent variables

Latent variables	Number of measurement variables	R^2
CSI	3	0.65
Loyalty	2	0.52

In ACSI, the R^2 of CSI is between 0.7 to 0.8 and the R^2 of loyalty is between 0.26 to 0.47. (Fornell et al., 1996)。

Table 3: Path coefficient of CSI model

Path	Path coefficient
Perceived quality → Perceived value	0.45*
Company image → Perceived value	0.30*
Perceived quality → CSI	0.47*
Perceived value → CSI	0.40*
CSI → Complaints	0.002
Company image → Loyalty	0.17*
CSI → Loyalty	0.57*
Complaints → Loyalty	0.03

* represents p-value <0.05

All the estimation of path coefficients were statistically significant except for the path coefficient related to complaints.

The only latent variable we will use to predict PBI is CSI. In the next section, we apply *t* test to verify that different primary bank index group holds different satisfaction level.

4.3. *t* test of satisfaction index between different PBI group

According the *t* test, the satisfaction level holds by different PBI group are statistically different, which indicates that CSI could be used to predict PBI. The detailed result of t-test was presented in table 4.

Table 4: T-test of satisfaction index between different PBI group

Group	Number	Mean	Std.	T-value	p-value
PBI = 0	438	3.40	1.04	6.56	<0.0001
PBI = 1	180	3.91	0.78		

4.4. Prediction of PBI through satisfaction index and demographic data

In this section, we will demonstrate our Primary Bank Index Model through data mining process. Among many data mining methods, we choose logit regression and artificial neural network (ANN) to illustrate our model.

4.4.1. Introduction of ANN

Artificial Neural Networks (ANNs) are a biologically inspired form of distributed computation. They simulate the functions of biological nervous systems. There are a large number of interconnected nodes that perform summation and thresholding. ANN have been successfully applied in different settings, including marketing, retail, banking and finance, insurance, telecommunications, operations management, and other industries (Smith and Gupta, 2000). An ANN can be organized in several different topologies and learning algorithms (Ref. (Lippmann, 1987)). The multi-layer perceptron (MLP) network is one of the most common used networks in financial research. Hence we use MLP to develop an ANN model in this paper. In the next section, we focus on the introduction of MLP networks.

4.4.2. Multi-layer perceptrons

The easiest way of transforming the input vector probably consists of introducing one or more layers of artificial neurons in the Perceptron architecture. Networks with more than one layer of artificial neurons, where only forward connections from the input towards the output are allowed, are called multi-layer perceptron (MLP) and the layers of nodes whose input and output are seen only by other nodes are termed hidden. An MLP with enough hidden layers and nodes can approximate any decision function to any arbitrary degree of accuracy. This feature is called the universality property. Further MLP concepts can be found in (Lippmann, 1987).

In order to overcome the over-fitting problem, usually the early stopping strategy is used. The method of early stopping tracks the network's performance using a separate validation set. Typically the error on the validation set will decrease as the network fits the data, and then increase as the network fits the idiosyncrasies of the noise of the training data.

4.4.3. Results of ANNs and logit regression model

In the original sample set, the ratio of who treat X Bank as their primary bank (PBI = 1) is only 0.29 (180/618), which might lead the data mining algorithms not to choose them in order to improve the overall performance. Thus, we duplicate the number of people who treat X Bank as their primary bank by a factor 2, which leads to the ratio of 0.45 (360/798). The description of sample set is summarized in table 5. Then, the sample set is divided into training set, validation set, and testing set with the proportion of 40%, 30%, and 30%. SAS Enterprise Miner 4.0 was used to run the predictive models.

Table 5: Data sample set summarization

	Original sample set		Weighted sample set	
	Number	Percent	Number	Percent
PBI = 0	438	70.9%	438	54.9%
PBI = 1	180	29.1%	360	45.1%

A standard three-layer ANN was used. There are seven nodes in the input layer, which is equal to the number of indicators (six demographic input variable + CSI variable). The output node is equal to 1, whereas the number of hidden nodes is determined by using the formula, $W \le M/6$, where W is the number of interconnection weights that satisfies the following equality:

$$W = (I + O) * H; \quad (1)$$

where M is the number of training examples, I the number of input nodes, O the number of output nodes, and H the number of hidden nodes. The size of the network is controlled by ensuring that the ratio of the number of training samples to the number of weights is equal to or larger than 6. Based on Eq. (1), the maximal number of hidden nodes is 7. Varying the number of hidden nodes from 4 to 7, it was determined that using six hidden nodes in the ANN gives the best performance.

The results of ANNs and logit regression on the test set are collated and given in table 6. In order to demonstrate the effect of CSI, we have a null model, which only includes demographic data as its input variables.

Table 6. Results of ANN and logit on the test set

	Full model accuracy rate (demographic + CSI)	Null model accuracy rate (demographic only)
ANN model	67.0%	58.2%
Logit model	63.2%	55.7%

It can be observed that the accuracy rate of full model (the one with CSI) is better than the null model whenever in ANN or logit regression model. This indicates that CSI variable has the predictive power towards PBI, it can forecast more accurately than only demographic data. On the other hand, as ANN can predict non-linear relationships, it performs better than logit model in this data set. Therefore, it can be concluded that CSI provide a promising predictive power in forecasting PBI.

5. Conclusion

In order to predict the potential value of customers for financial bank, a PBI was proposed. Researchers have shown demographic variable are important determinants in the acquisition of financial services. On the other hand, CSI is also a good index to predict PBI. Thus, in this study, we use demographic data and CSI to predict PBI. It has been shown with the existence of CSI, the prediction rate can improve 8.8% for ANN and 7.5% for logit regression model, which concludes the predictive power of CSI. Still, the overall prediction rate is not good enough, 67% for ANN and 63.2% for logit regression model. We will discuss how to improve it in the next section.

The contributions of this study is as follows: Firstly, a CSI model for Taiwan was proposed, Secondly, a primary bank index (PBI) was proposed and treat it as a proxy of potential contributions of customers, Thirdly, we integrate CSI study with CRM study by using satisfaction scores derived from CSI model to predict the PBI, and finally, a PBI predictive model was proposed for future study.

5.1. Research limitations and suggestions for future research

Due to the lack of customers' transaction data, we only use demographic data and satisfaction index to demonstrate the predictive model. Still, we have the acceptable hit-rate about 67 %. After interviewing some professionals in financial service industry, they indicate CSI variable is just one of the concerns that customers will choose the bank as their primary bank. In addition, we also refer to some literatures for theoretical supports. In the future research we suggest to incorporate transaction data with the following variables:

1. Sustaining period: According to Bolton (1998), the longer a customer stays with a

bank, the more products he will buy and he will contribute more profits to the bank. Therefore, we conclude that the earlier a customer starts relationship with a bank, the more possibility he will regard it as his primary bank. We suggest a variable vintage= (date- relationship start date)/30, using month as counting unit.

2. Automatic payment account: If a customer pays some bills through his automatic payment account in a bank, he probably deals with it more often than other banks. Therefore, we assume he would more likely regard the bank as his primary bank.

3. Going to the counter to pay public service spending: As the premise of the third item, we assume a customer would pay the public service spending in his primary bank.

4. Salary transferring amounts: For customers with salary transfer accounts, we can observe their behavior after their salaries are deposited into their account. They may transfer their salaries to other accounts immediately or keep them in the current banks. The less a customer transfers his salary out of his bank, the more possibility that he regards it as his primary bank.

5. Profit contribution: We assume if a customer contributes more profit to a bank, he would more like regard it as his primary bank. All banks have a formula to calculate customers' profit contribution, taking revenue and cost into account.

6. Total transaction amount: The larger a customer's total transaction amount with a bank, the more possibility he would regard it as his primary bank.

7. Product Category: Besides transaction-related variables mentioned earlier, we introduce another model FRAC stated by Kestnbaum (Kestnbaum et al., 1998). It is believed that product category held by customers will also influence their attitude towards the bank. We categorize all financial service products into six categories-current accounting、savings account、investment、insurance、pensions and borrowing, trying to analyze what kind of products will motivate customers to take the bank as their primary bank.

8. Amounts of products held: The more product items the customer has, the more possibility he would regard the bank as his primary bank.

Appendix A: Sample characteristics (N=618)

		PBI = 1 Customers(N=180)		**PBI = 0 Customers(N=438)**	
	Explanation	No.	%	No.	%
Sex	Male	82	45.56	200	45.66
	Female	98	54.44	238	54.34
Marriage	Single	68	37.78	132	30.14
	Married	111	61.67	303	69.18
	No answer	1	0.56	3	0.68
Monthly Income	Below $20,000	18	10	28	6.39
	$20,001-30,000	24	13.33	61	13.93
	$30,001-40,000	25	13.89	70	15.98
	$40,001-50,000	19	10.56	59	13.47
	$50,001-60,000	11	6.11	32	7.31
	$60,001-80,000	8	4.44	33	7.53
	$80,001-100,000	4	2.22	11	2.51
	Above $100,001	7	3.89	32	7.31
	No answer	14	7.78	36	8.22
	No income	50	27.78	76	17.35
Education	Elementary School/Below	12	6.67	23	5.25
	Junior High School	20	11.11	36	8.22
	High School	58	32.22	153	34.93
	College	82	45.56	206	47.03
	Master/Above	7	3.89	19	4.34
	No data	1	0.56	1	0.23
Age	Less than 20	20	11.11	12	2.74
	21 30	56	31.11	113	25.8
	31 40	36	20	133	30.37
	41 50	34	18.89	98	22.37
	51 60	12	6.67	35	7.99
	Above 61	19	10.56	29	6.62
	No data	3	1.67	18	4.11
Occupation	Government staff	9	5	44	10.05
	White-collar Management	5	2.78	21	4.79

	White-collar staff	25	13.89	78	17.81
	Factory management	2	1.11	9	2.05
	Blue-collar labor	26	14.44	62	14.16
	Business owner	6	3.33	34	7.76
	Home keeper	31	17.22	58	13.24
	Free lancer	12	6.67	25	5.71
	Military & Police	3	1.67	5	1.14
	Students	26	14.44	20	4.57
	Farmer/Fisherman	0	0	1	0.23
	Specialist	9	5	27	6.16
	Retired/graduated not work yet	22	12.22	41	9.36
	Teacher	4	2.22	5	1.14
	Nurse	0	0	4	0.91
	No answer	0	0	4	0.91

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