Hindawi Publishing Corporation
Mathematical Problems in Engineering
Volume 2016, Article ID 1475148, 9 pages
http://dx.doi.org/10.1155/2016/1475148

Research Article

An Analysis of Bank Service Satisfaction Based on Quantile Regression and Grey Relational Analysis

Wen-Tsao Pan and Yungho Leu

Department of Information Management, National Taiwan University of Science and Technology, Taipei 10607, Taiwan

Correspondence should be addressed to Yungho Leu; yhl@cs.ntust.edu.tw

Received 6 January 2016; Accepted 13 March 2016

Academic Editor: Feng Yang

Bank service satisfaction is vital to the success of a bank. In this paper, we propose to use the grey relational analysis to gauge the levels of service satisfaction of the banks. With the grey relational analysis, we compared the effects of different variables on service satisfaction. We gave ranks to the banks according to their levels of service satisfaction. We further used the quantile regression model to find the variables that affected the satisfaction of a customer at a specific quantile of satisfaction level. The result of the quantile regression analysis provided a bank manager with information to formulate policies to further promote satisfaction of the customers at different quantiles of satisfaction level. We also compared the prediction accuracies of the regression models at different quantiles. The experiment result showed that, among the seven quantile regression models, the median regression model has the best performance in terms of RMSE, RTIC, and CE performance measures.

1. Introduction

In response to the requirement of opening market and to promote the economic growth, Taiwanese government has actively formulated policies to promote the financial liberalization in Taiwan. As a result, many mergers of different banks have occurred in the past few years. Bank mergers may change the perception of a customer on the service quality of a bank. Therefore, a bank manager should improve the service quality of his clerks in order to promote the customer's satisfaction. High customer satisfaction on a bank can attract customers to continue doing their business with the bank and thus establishes the customers' loyalty to the bank. To effectively improve the service quality of a bank so as to promote the customer's satisfaction has become an important issue of the banking industry today.

Different from the existing studies on bank service satisfaction [1, 2], we use the data on service satisfaction of the public and private banks in Taiwan in this study. The questionnaire for data collection was designed by the Louis Harris International in 1995. In this study, we first collected the data on service satisfaction using the questionnaire. Then, we used the grey relational analysis to examine the customer satisfaction on the service of the banks, including the public and the private banks in Taiwan. With the grey relational analysis, we found the variables that affected the levels of service satisfaction of the public banks and the private banks. We also ranked the banks according to their levels of service satisfaction. Finally, we conducted a quantile regression analysis on the 36 banks of the dataset to find the variables that affected the levels of satisfaction for customers at different quantiles of service satisfaction. The results can be used by a bank manager to formulate different policies to further promote the satisfaction of the customers at different quantile of service satisfaction. Finally, we compared the performance of different quantile regressions in terms of three different measures of performance evaluation.

The remainder of this paper is organized as follows. Section 1 introduces the research motivation and purpose. Section 2 reviews the literature on grey theory and quantile regression. Section 3 discusses the dataset and results of the empirical study. Section 4 gives the conclusion and the suggestion of this paper.

2. Research Method

2.1. Grey Relational Analysis. First proposed by Deng [3], the grey relational analysis can be used to measure the similarity

Table 1: An example dataset.

Sequence	$k = 1$	$k = 2$	$k = 3$	$k = 4$	$k = 5$	$k = 6$
x_0	1.000	1.100	2.000	2.250	3.000	4.000
x_1	1.000	1.166	1.834	2.000	2.340	3.000
x_2	1.000	1.125	1.075	1.375	1.625	1.750
x_3	1.000	1.000	0.700	0.800	0.900	1.200

between two sequences of factors. Assume that the state of a system can be modeled by a sequence of factors. Two system states are said to be similar if the values of their corresponding factors are similar. In a real life application, a standard sequence is selected to calculate the relational grades of a set of inspected sequences. Usually, the standard sequence is composed of the maximal values of each of the factors in the current dataset. By referring to the standard sequence, the grey relational analysis gives each inspected sequence a grey relational grade (GRG). The more an inspected sequence is similar to the standard sequence, the larger the GRG of the inspected sequence is. Since the standard sequence usually represents a state of the system with maximum performance, a sequence with a large GRG is therefore better than a sequence with a small GRG. The grey relational analysis has been widely used in performance evaluation [4–6].

The grey relational grade of an inspected sequence is calculated through the following steps.

Step 1 (define the sequences). To perform the grey relational analysis, we need to define the sequences for comparison. To illustrate, we use Table 1 as an example. Each column in Table 1 represents a factor of the system state while each row in Table 1 represents a sequence of the system state. Among all the sequences of the system state, we choose or create a sequence, called the standard sequence, to measure the performance of the other sequences which are called the inspected sequences. A sequence x_i is denoted by a set $\{x_i(k) \mid k = 1, \ldots, n\}$. Without loss of generality, we choose x_0 as the standard sequence.

Step 2 (standardization). Since different factors may have different ranges of values which are not comparable, we need to standardize the values of all factors so that values from different factors are comparable. One way of standardization is to divide all the values of a factor by the maximum value of the factor. By doing so, values of all factors are all less than one and greater than zero.

Step 3 (calculate the grey relational coefficients). The grey relational coefficient of the kth factor of sequence x_i is calculated by the following equation:

$$\xi_i(k) = \frac{\min_i \min_k |x_0(k) - x_i(k)| + \rho \max_i \max_k |x_0(k) - x_i(k)|}{|x_0(k) - x_i(k)| + \rho \max_i \max_k |x_0(k) - x_i(k)|}. \quad (1)$$

Let $\Delta_{0i}(k)$ denote $|x_0(k) - x_i(k)|$. Equation (1) can be written as

$$\xi_i(k) = \frac{\min_i \min_k \Delta_{0i}(k) + \rho \max_i \max_k \Delta_{0i}(k)}{|x_0(k) - x_i(k)| + \rho \max_i \max_k \Delta_{0i}(k)}. \quad (2)$$

Note that to find the value of $\min_i \min_k \Delta_{0i}(k)$, we find, for inspected sequence x_i, the minimum value of the differences between factor k of x_0 and factor k of x_i, $k = 1$ to n. Then, we find the minimum value among the minimum values of all the inspected sequences. The value of $\max_i \max_k |x_0(k) - x_i(k)|$ can be found in a similar way. The rationale behind (2) is that we use the global minimum and the global maximum of the componentwise differences between the standard sequence and all the inspected sequences to rescale the difference between a factor of an inspected sequence and the same factor of the standard sequence. And then, we use the rescaled differences, also called the grey relational coefficients, to replace the values of the original factors. The value of ρ belongs to $(0, \infty)$ and is usually set to 0.5.

Step 4 (find the grey relational grade). The grey relational grade r_i of inspected sequence x_i is defined to be the average of all its grey relational coefficients. The grey relational grade r_i of x_i is calculated according to the following equation:

$$r_i = \frac{1}{n} \sum_{k=1}^{n} \xi_i(k). \quad (3)$$

To illustrate how to calculate the grey relational grade of an inspected sequence, we use the dataset in Table 1.

Step 1 (define the sequence). We assume that x_0 is the standard sequence.

Step 2 (standardization). We assume that the factors of the dataset in Table 1 are comparable. No standardization is required.

Step 3 (calculate the grey relational coefficients). The componentwise differences between the standard sequence and all the inspected sequences are shown in the following:

(1) Componentwise differences between x_0 and x_1:

$$\begin{aligned} \Delta_{01}(1) &= 0.000, \\ \Delta_{01}(2) &= 0.066, \\ \Delta_{01}(3) &= 0.166, \\ \Delta_{01}(4) &= 0.250, \\ \Delta_{01}(5) &= 0.660, \\ \Delta_{01}(6) &= 1.000. \end{aligned} \quad (4)$$

(2) Componentwise differences between x_0 and x_2:

$$\begin{aligned} \Delta_{02}(1) &= 0.000, \\ \Delta_{02}(2) &= 0.025, \\ \Delta_{02}(3) &= 0.925, \\ \Delta_{02}(4) &= 0.875, \\ \Delta_{02}(5) &= 1.375, \\ \Delta_{02}(6) &= 2.250. \end{aligned} \tag{5}$$

(3) Componentwise differences between x_0 and x_3:

$$\begin{aligned} \Delta_{03}(1) &= 0.000, \\ \Delta_{03}(2) &= 0.100, \\ \Delta_{03}(3) &= 1.300, \\ \Delta_{03}(4) &= 1.450, \\ \Delta_{03}(5) &= 2.100, \\ \Delta_{03}(6) &= 2.800. \end{aligned} \tag{6}$$

We find the following vectors of differences:

(1) $\Delta_{01} = (0.000, 0.066, 0.166, 0.250, 0.660, 1.000)$;

(2) $\Delta_{02} = (0.000, 0.025, 0.925, 0.875, 1.375, 2.250)$;

(3) $\Delta_{03} = (0.000, 0.100, 1.300, 1.450, 2.100, 2.800)$.

The global minimum and the global maximum of all the differences are 0.000 and 2.800, respectively. Let $\rho = 0.5$. We write

$$\xi_i(k) = \frac{0 + (0.5) \times (2.8)}{\Delta_{0i}(k) + (0.5) \times (2.8)}. \tag{7}$$

We then calculate the grey relational coefficients of the inspected sequence x_1 in the following:

$$\begin{aligned} \xi_1(1) &= 1.000, \\ \xi_1(2) &= 0.9549, \\ \xi_1(3) &= 0.8939, \\ \xi_1(4) &= 0.8484, \\ \xi_1(5) &= 0.6796, \\ \xi_1(6) &= 0.5833. \end{aligned} \tag{8}$$

Finally, we find the grey relational grade (GRG) of the inspected sequence x_1 in the following:

$$\begin{aligned} r_1 = \frac{1}{6}(1 + 0.9549 + 0.8939 + 0.8484 + 0.6796 \\ + 0.5833) = 0.8266. \end{aligned} \tag{9}$$

The grey relational grades of sequences x_2 and x_3 can be found in the same way.

2.2. Quantile Regression. Koenker and Bassett [7] proposed the quantile regression method. Quantile regression is used to explore the effects of explanatory variables (X) on the explained variable (Y) at different quantiles of the explained variable. Different from the conventional linear models (such as the least squares method) that predict the mean of the explained variable given a specific value of each explanatory variable, a quantile regression model predicts the value of the explained variable at a specific quantile of the explained variable giving a specific value of each explanatory variable. Therefore, the quantile regression method facilitates the study of the effects of the explanatory variables on different quantiles of the explained variable. The quantile regression method has been widely used in many applications [8–10].

3. Empirical Analysis

3.1. Sample Dataset and Variables. Based on a questionnaire designed by the Louis Harris International Taiwan, we conducted a survey on the bank service quality of Taiwan in 2013. We analyzed the satisfaction of bank service in Taiwan by using the collected questionnaire data. The dataset consists of 8 public banks and 28 private banks. The variables designed for bank service satisfaction include "clerk service attitude" ($X1$), "customer-oriented service" ($X2$), "flexibility in handling customer inquiries" ($X3$), "service efficiency" ($X4$), "interest rate favoring customers" ($X5$), "transaction errors" ($X6$), "convenience of branch locations" ($X7$), "service traffic flow" ($X8$), and "service counter design" ($X9$). The value of each variable of a bank is obtained by averaging the scores of the same variable on all the questionnaires for the bank. The dataset for the public bank is shown in Table 2. The descriptive statistics of the variables are shown in Table 3. The source dataset is divided into three datasets. The first dataset contains all the 36 banks including the private and public banks; the second dataset contains only the 28 private banks; the third dataset contains the 8 public banks whose data are shown in Table 2.

3.2. Grey Relational Analysis on Bank Service Satisfaction. This study applied the Matlab tool box for grey relational analysis [11] to obtain a grey relational grade (GRG) for a bank to represent the level of satisfaction of the bank. In this study, we performed two analyses using the grey relational analysis. In the first analysis, we used the grey relational analysis to find the satisfaction levels of different variables. To do that, we first transposed the dataset so that the samples of the dataset become the variables and the variables become the samples of the transposed dataset. Figures 1(a) and 1(b) show the results of grey relational analysis for the eight public banks and the 28 private banks, respectively. The bold dotted lines represent the standard sequences and the thin lines represent the inspected sequences, which are samples to be evaluated. The more an inspected sequence is close to the standard sequence, the larger its satisfaction grade is. According to Figure 1(a), the top three most satisfied variables among the nine surveyed variables for the public banks are "convenience of branch locations" (GRG = 0.8775),

Table 2: The dataset for public banks.

Bank names	$X1$	$X2$	$X3$	$X4$	$X5$	$X6$	$X7$	$X8$	$X9$
Farmers Bank of China	4.31	3.63	3.67	3.89	3.31	4.52	3.82	3.7	3.84
Land Bank of Taiwan	3.98	3.44	3.52	3.74	3.77	4.62	2.67	2.87	3.65
First Commercial Bank	4.04	3.52	3.31	3.73	3.41	4.63	3.61	3.29	3.31
Taiwan Business Bank	3.69	3.14	3.21	3.38	3.28	4.81	3.64	3.09	4
Bank of Taiwan	3.86	3.24	3.44	3.67	3.16	4.67	3.08	3.19	3.95
Hua Nan Bank	3.83	3.12	3.28	3.63	2.92	4.57	3.92	3.25	3.35
Chang Hwa Bank	3.53	2.88	3.01	3.53	2.72	4.78	3.6	3.25	3.8
Taiwan Cooperative Bank	3.41	2.85	3.1	3.03	3.06	4.46	3.57	3.12	2.89

Table 3: Descriptive statistics of the variables in three different groups of data.

	Variables	$X1$	$X2$	$X3$	$X4$	$X5$	$X6$	$X7$	$X8$	$X9$
First dataset (36)	Max.	4.65	4.02	4.06	4.29	4.12	4.92	3.98	4.16	4.63
	Min.	3.10	2.68	2.96	2.80	2.72	3.28	2.67	2.87	2.89
	Avg.	3.97	3.38	3.46	3.66	3.39	4.41	3.45	3.46	3.80
	Std.	0.34	0.28	0.23	0.33	0.29	0.46	0.33	0.30	0.39
Second dataset (28)	Max.	4.65	4.02	4.06	4.29	4.12	4.92	3.98	4.16	4.63
	Min.	3.10	2.68	2.96	2.80	3.00	3.28	2.81	2.94	3.02
	Avg.	4.01	3.42	3.50	3.69	3.44	4.34	3.44	3.53	3.85
	Std.	0.34	0.27	0.22	0.34	0.27	0.50	0.32	0.29	0.37
Third dataset (8)	Max.	4.31	3.63	3.67	3.89	3.77	4.81	3.92	3.70	4.00
	Min.	3.41	2.85	3.01	3.03	2.72	4.46	2.67	2.87	2.89
	Avg.	3.83	3.23	3.32	3.58	3.20	4.63	3.49	3.22	3.60
	Std.	0.27	0.27	0.20	0.25	0.30	0.11	0.39	0.22	0.36

"clerk service attitude" (GRG = 0.5607), and "service traffic flow" (GRG = 0.509), while the three least satisfied variables are "customer-oriented service" (GRG = 0.4364), "service counter design" (GRG = 0.434), and "transaction errors" (GRG = 0.4338).

In contrast, Figure 1(b) shows that, for the 28 private banks, the top three most satisfied variables are "convenience of branch locations" (GRG = 0.94), "clerk service attitude" (GRG = 0.7302), and "service traffic flow" (GRG = 0.6594), while the three least satisfied variables are "transaction errors" (GRG = 0.5266), "service efficiency" (GRG = 0.5207), and "customer-oriented service" (GRG = 0.5038). Therefore, in regard to their advantages, both the private and public banks enjoyed "branch locations," "clerk service attitude," and "service traffic flow." In regard to their disadvantages, both public and private banks need to improve their "customer-oriented service" and "transaction errors." Furthermore, the "service efficiency" for the private banks and the "counter design" for the public banks need to be improved too.

In the second analysis, we compare the service satisfaction of different banks. Figure 2(a) shows the result of the grey relational analysis for the eight public banks. It shows that the top three banks in terms of service satisfaction are "Farmers Bank of China" (GRG = 0.8857), "Land Bank of Taiwan" (GRG = 0.6933), and "First Commercial Bank" (GRG = 0.6841); the bottom three banks are "Hua Nan Bank" (GRG = 0.6307), "Chang Hwa Bank" (GRG = 0.5996), and "Taiwan Cooperative Bank" (GRG = 0.4932). Figure 2(b) shows the grey relational analysis for the 28 private banks. It shows that the top three banks in terms of service satisfaction are "E.SUN Commercial Bank" (GRG = 0.8586), "Union Bank of Taiwan" (GRG = 0.8138), and "Yuanta Commercial Bank" (GRG = 0.7916); the bottom three banks included "Bank of Taipei" (GRG = 0.4669), "Jih Sun International Commercial Bank" (GRG = 0.4521), and "Mega International Commercial Bank" (GRG = 0.4342).

Lastly, we perform grey relational analysis on all the 36 banks, including the public and private banks. Figure 2(c) shows that the top three banks, among both public and private banks, are "E.SUN Commercial Bank" (GRG = 0.8643), "Union Bank of Taiwan" (GRG = 0.8217), and "Yuanta Commercial Bank" (GRG = 0.7993). Note that all of them are private banks. On the other hand, the bottom three banks include one public bank and two private banks which are "Taiwan Cooperative Bank" (GRG = 0.4773), "Jih Sun International Commercial Bank" (GRG = 0.4666), and "Mega International Commercial Bank" (GRG = 0.4483). Therefore, according to the above analysis, private banks usually receive better service satisfaction from their customers than public banks do.

3.3. Quantile Regression Analysis of Different Factors on Service Satisfaction. In addition to the grey relational analysis, in this study we perform quantile regression analysis to explore the factors that influence service satisfaction for

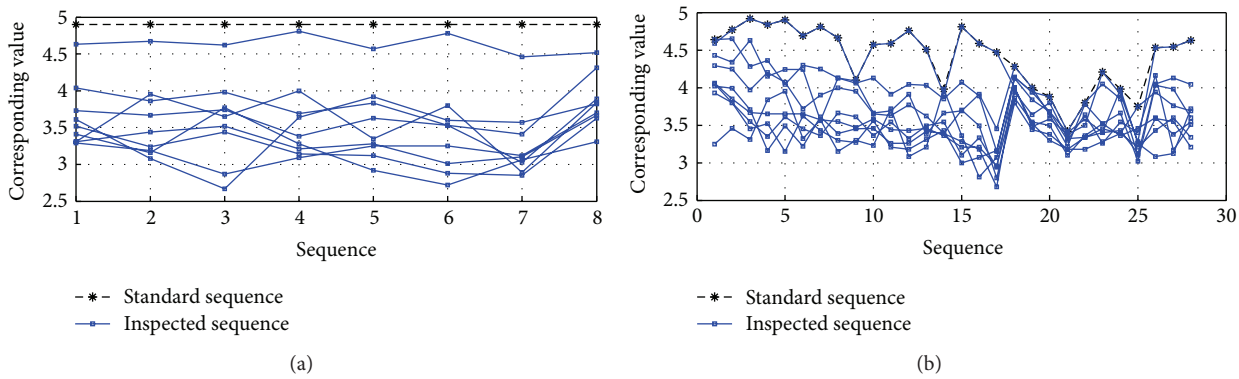

Figure 1: Results of grey relational analysis for different surveyed variables.

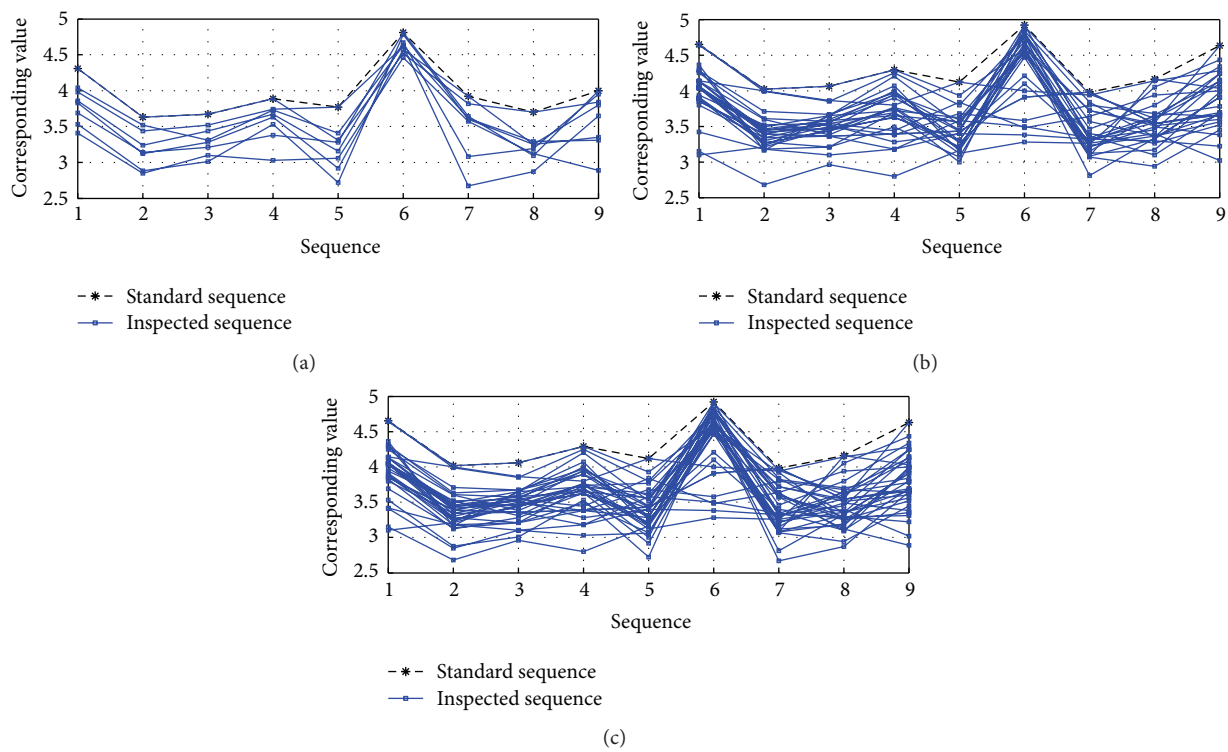

Figure 2: Grey relational analysis on the satisfaction of eight public banks (a), 28 private banks (b), and all 36 banks (c).

those samples with low-, medium-, and high-levels of service satisfaction. To do that, we discretize the values of all the variables into five intervals. Each value of a variable is transformed into its corresponding label of the interval. In this study, the top 20 percent values of a variable are given the largest label, which is 5, and so on. The transformed dataset for the public banks is shown in Table 4. Note that, in Table 4, GRG denotes the grey relational grade of a sample bank.

In this study, we use the STATA software to conduct the 0.25 quantile, median, and 0.75 quantile regressions on the dataset of all the 36 banks. By using grey relational grades of the above grey relational analysis as the dependent variables (Y) and nine bank service satisfaction-related variables as the independent variables ($X1$–$X9$) for quantile regression analysis, this study determined which questionnaire survey question items (variables) affected the bank service satisfaction performance for the customers at a specific quantile of service satisfaction. The quantile regression analysis is conducted mainly for three different quantiles including the 0.25 quantile, median, and 0.75 quantile. According to the analysis results shown in Table 5, "bank clerk service attitude" ($X1$), "customer-oriented service" ($X2$), and "flexibility in handling customer inquiries" ($X3$) had no effects on the bank service satisfaction performance at different quantiles of service satisfaction. However, for "service efficiency" ($X4$), its coefficient is significantly different from zero at 10% significance level for all different quantile regression models. This result indicates that the waiting time for bank service would affect the levels of service satisfaction for customers with different levels of service satisfaction. Regarding

Table 4: The transformed dataset of the public bank dataset.

Bank names	$X1$	$X2$	$X3$	$X4$	$X5$	$X6$	$X7$	$X8$	$X9$	GRG
Farmers Bank of China	5	5	5	5	3	1	5	5	5	0.8857
Land Bank of Taiwan	4	4	4	5	5	3	1	1	4	0.6933
First Commercial Bank	4	5	3	5	4	3	4	3	2	0.6841
Taiwan Business Bank	2	2	2	3	3	5	4	2	5	0.6525
Bank of Taiwan	3	3	4	4	3	3	2	2	5	0.6631
Hua Nan Bank	3	2	3	4	1	2	5	3	3	0.6307
Chang Hwa Bank	1	1	1	3	1	5	4	3	5	0.5996
Taiwan Cooperative Bank	1	1	1	1	2	4	4	2	1	0.4932

Table 5: Quantile regression coefficients at different quantiles.

Var.	Model											
	OLS Adj. $R^2 = 0.9528$			Q0.25 Pseudo $R^2 = 0.8246$			Q0.5 Pseudo $R^2 = 0.8135$			Q0.75 Pseudo $R^2 = 0.8304$		
	Coef.	T	Sig.	Coef.	T	Sig.	Coef.	T	Sig.	Coef.	T	Sig.
$X1$	−0.042	−1.62		−0.038	−0.75		−0.044	−1.33		−0.0492	−0.96	
$X2$	0.072	2.58	*	0.068	1.46		0.062	1.52		0.075	1.14	
$X3$	0.064	1.49		0.102	1.55		0.057	0.69		−0.003	−0.03	
$X4$	0.059	2.5	*	0.054	1.88	∧	0.051	2.01	∧	0.085	2.02	∧
$X5$	0.085	3.37	**	0.073	3.98	**	0.071	2.53	*	0.128	2.89	**
$X6$	0.071	4.98	**	0.062	3.62	**	0.065	3.27	**	0.083	3.23	**
$X7$	0.060	5.05	**	0.065	7.32	**	0.063	4.53	**	0.057	2.24	*
$X8$	0.055	2.62	*	0.044	2.38	*	0.041	1.5		0.044	0.94	
$X9$	0.050	3.39	**	0.042	2.94	**	0.056	3.4	**	0.038	1.19	

Note: ∧ means that it is significant under 10% significance level; * means that it is significant under 5% significance level; ** means that it is significant under 1% significance level.

the variable of "interest rate favoring customers" ($X5$), according to Table 5, its coefficient is different from zero at 1% significance level in all the three quantile regression models. Figure 3 shows that, for the customers at the 0.75 quantile of service satisfaction, the ordinary least squares (OLS) (the dash line on the plot) regression tends to underestimate the effect of "interest rate favoring customers" ($X5$) on service satisfaction. Therefore, customers with a high level of service satisfaction will be especially concerned about whether the bank can adjust the interest rates to their advantages. This signifies that a bank manager needs to pay more attention to the policy of interest rate adjustment to further promote the service satisfaction of his customers who already have a high level of service satisfaction.

For the variable of "transaction errors" ($X6$), Table 5 shows that its coefficients are different from zero for all the three different quantile regression models at 1% significance level. Furthermore, Figure 3 shows that for high quantiles of service satisfaction the ordinary least squares regression model tends to underestimate the effect of $X6$. Figure 4 shows the results of 0.25, 0.5, and 0.75 quantile regression models in terms of $X6$ and $(X6)^2$ (stands for $X6$ squared). In the plot, the satisfaction levels are calculated according to the regressed quadratic equations of variable $X6$. The trends of the curves indicate that fewer transaction errors would result in higher satisfaction levels (in terms of GRG). Note that a large value of $X6$ in Figure 4 represents a case with fewer transaction errors and, therefore, receives a higher satisfaction level from the customers. Also note that, for the median regression model, the level of service satisfaction increases as the number of transaction errors decreases. However, the trend is reversed as the number of transaction errors is further reduced to be below a certain number, a case that is counter to our intuition. This represents that the quadric equation of $X6$ is not adequate to capture the relationship between the service satisfaction levels and $X6$.

Table 5 shows that the coefficient of $X7$ (convenience of branch location) is significantly different from zero at 1% significance level for both 0.25 quantile and median regression models. For the 0.75 quantile regression model, its coefficient is significantly different from zero at 5% significance level. The results show that the convenience of branch location can affect the service satisfaction, regardless of different quantiles of service satisfaction. In addition, Figure 3 shows that the ordinary least squares regression overestimates the effect of $X7$ on service satisfaction for high quantiles of service satisfaction. As to the variable of "service traffic flow" ($X8$), Table 5 shows that its coefficient is different from zero only for the 0.25 quantile regression model at 5% significance level. In other words, improving the service traffic flow can promote the service satisfaction for customers with low levels of service satisfaction. Finally, regarding "service counter

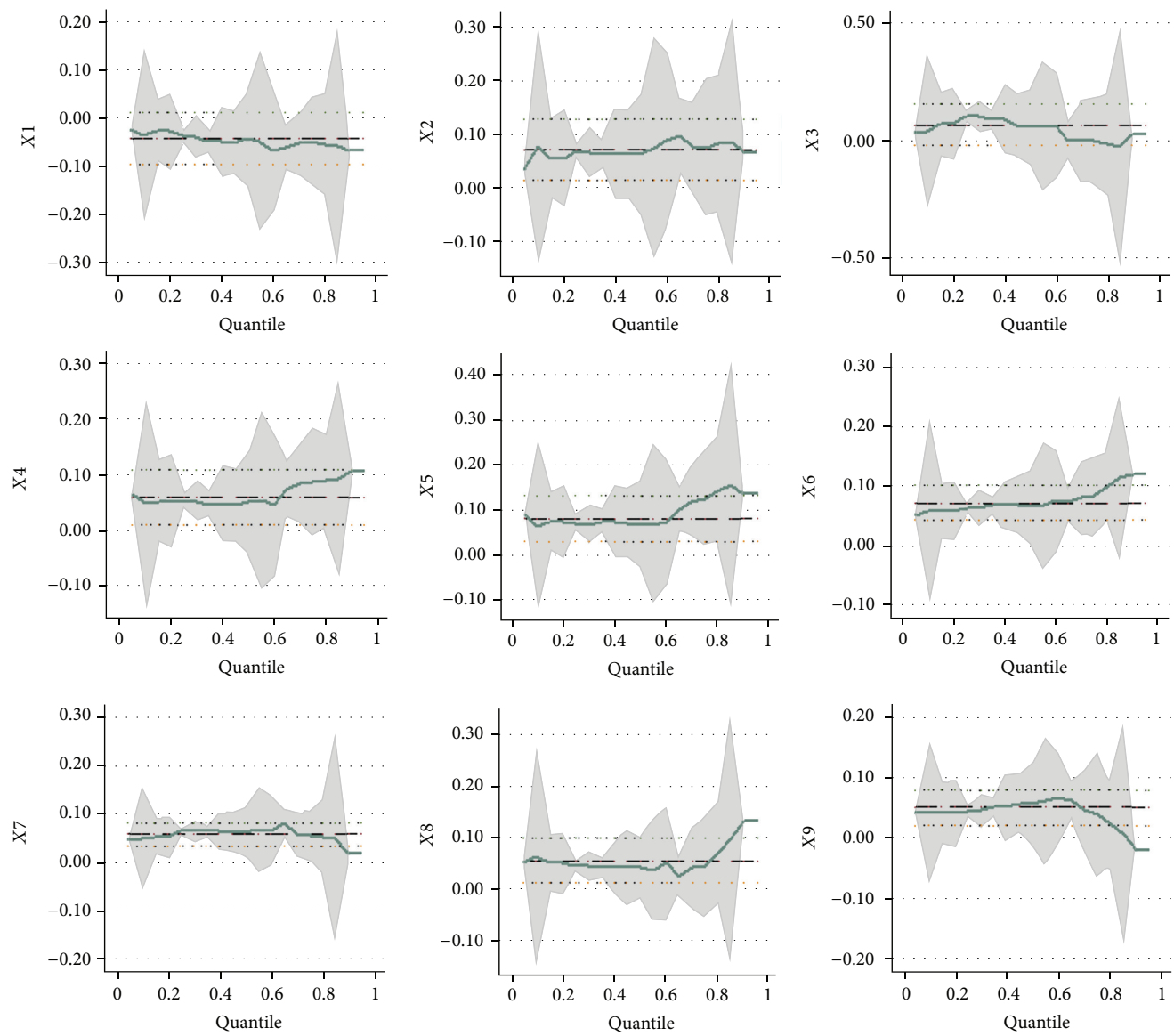

Figure 3: Satisfaction performance results of all 36 banks.

design" ($X9$), its coefficients are different from zero for the 0.25 and 0.5 quantile regression at 1% significance level. Therefore, customers with low or medium levels of service satisfaction care more about the "service counter design" and to improve the design of the service counter may further promote the service satisfaction of the customers with low to medium levels of service satisfaction. The comprehensive analysis of the effects of different variables in this study could help a bank manager to promote the service satisfaction of his customers with different levels of service satisfaction.

3.4. Performance Comparison of Different Quantile Regression Models. Finally, by using the grey relational grade as the dependent variables (Y) and the nine bank service satisfaction-related variables as the independent variables ($X1$–$X9$), this study built seven forecasting models, including Q15, Q25, Q35, Q50, Q65, Q75, and Q85. 5-fold cross-validation is used to find the values of performance measures of the seven models. To perform 5-fold cross-validation, thirty-six samples of the dataset are divided into five groups. Four groups of them are used to build a model and the rest is used as a test dataset to calculate the values of different performance measures. This procedure is repeated for five times each with a different group of the dataset as the test dataset. The five values of a performance measure are averaged to render the reported value of the performance measure. The performance measures for this study include RMSE, RTIC, and CE [12]. The equations for these measures are as follows.

The equation for RMSE (Root Mean Squared Error) is

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{t=1}^{N} \left(x_t - \widehat{x_t}\right)^2}{N}}. \tag{10}$$

Table 6: Performance of the seven quantile regression models.

Index	Q15	Q25	Q35	Q50	Q65	Q75	Q85
RMSE	0.04227	0.03610	0.12830	0.03494	0.03906	0.04014	0.08812
RTIC	0.00519	0.00372	0.03859	0.00338	0.00412	0.00434	0.02032
CE	0.74438	0.78248	0.12402	0.84030	0.83163	0.82688	0.18862

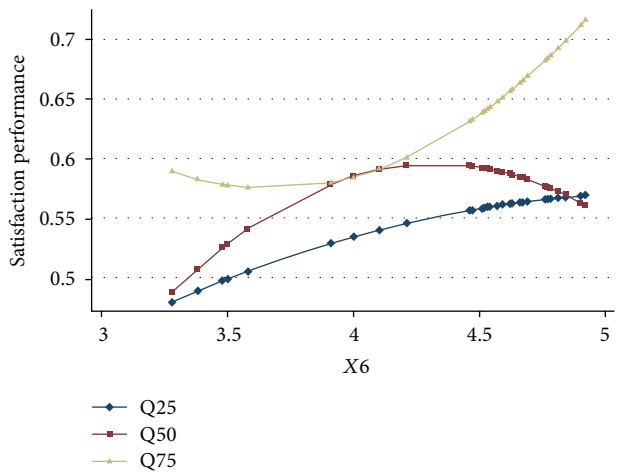

Figure 4: Regressed curves for different quantiles in terms of $X6$.

The equation for RTIC (Revision Theil Inequality Coefficient) is

$$\mathrm{RTIC} = \sqrt{\frac{\sum_{t=1}^{N}\left(x_t - \widehat{x_t}\right)^2}{\sum_{t=1}^{N} x_t^{\,2}}}. \tag{11}$$

The equation for CE (coefficient of efficiency) is

$$\mathrm{CE} = 1 - \frac{\sum_{t=1}^{N}\left(x_t - \widehat{x_t}\right)^2}{\sum_{t=1}^{N}\left(x_t - \overline{x_t}\right)^2}. \tag{12}$$

Note that a model with small values of RMSE and RITC performs better than a model with large values of RMSE and RITC. For CE, a good forecasting model has a CE value close to 1. The performance of the seven quantile regression models is shown in Table 6.

Table 6 shows that the median regression model has the smallest RMSE and RTIC values and the largest CE value. Therefore, the median regression model has the best prediction accuracy among all the seven quantile regression models.

4. Conclusion and Suggestion

The major contribution of this paper is to explore bank service satisfaction performance based on the 2013 service satisfaction survey data of 36 public and private banks in Taiwan. This paper proposes to use the grey relational analysis to gauge the service satisfaction of a customer based on nine question items in a questionnaire. With the grey relational analysis, we have found some variables that contribute more on the service satisfaction of customers than the other variables. We also ranked the banks according to their grey relational grades of satisfaction levels. Furthermore, the quantile regression analysis was used to further explore the determinant factors of service satisfaction for the customers at different quantiles of service satisfactions. With regressions on different quantiles, the manager of a bank can find the factors that are more concerned by their customers at a specific quantile of service satisfaction. As a result, the manager can formulate different policies to promote the service satisfaction of customers at different quantiles of service satisfaction. Finally, this study examined the performance of different regression models. The experimental result showed that, among the seven quantile regression models, the median regression model has the best performance in terms of RMSE, RTIC, and CE performance measures.

Competing Interests

The authors declare that they have no competing interests.

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