Modelling the drivers of Net Promoter Score – An examination using the EPSI Rating Framework

Johan Parmler (PhD)[1]*, Jacob Hallencreutz (PhD)[1] and Fredrik Host[1]

[1]EPSI Research Services, EPSI Research Services Ltd, London: 33 st. James Square, London SW1Y 4JS, England

*Corresponding author: Tel: 46-8-31-5300. E-mail: johan.parmler@epsi-rating.com

Abstract

The concept of Net Promoter Score (NPS) has become a popular method of satisfaction and loyalty measurement, mainly due to its simplicity. Essentially, NPS measures a customer's willingness to recommend a given firm. It has its genesis in the original article by Frederick Reichheld ("The one number you need to grow," Harvard Business Review, December 2003). The NPS approach is widely diffused and adopted due to its simplicity. It is based on the questions of "likelihood to recommend the company to friend or colleague" (*Rec*) using the scale 0=extremely unlikely, 10=extremely likely. *Rec* is than used to determine if a customer is a detractor (*Rec*=0-6), passive (*Rec*=7-8) or promoter (*Rec*=9-10). It's strength as a non-financial performance indicators have been criticized since it is unclear what actually affects the score. Thus, how could a driver analysis for a satisfaction measure like NPS be conducted? This paper uses customer survey data from EPSI Rating and uses an ordinal logistic regression approach. This approach has several advantages over using the conventional method of linear regression models. First, it is more meaningful for companies to know whether certain aspects of customer perception have significant impacts on converting customers to become more loyal i.e., (detractors, passive, and promoters). Second, the model takes non-uniform effect into account which is very important from a managerial perspective. This can sharpen organizations' focus by knowing that some of the predictors may have a greater effect on pushing customers away from detractors, and others may have a greater effect on developing customers into promoters.

It should be mentioned that the usability of NPS as a business performance measure has been questionable (Kristensen, et al., 2014). The focus of this study, however, is neither to argue whether NPS is a superior metric to other loyalty measures nor to defend NPS as the only number that companies should attend to. Instead, we focus on presenting a method to improve organizations' performances in order to increase the number of promoters and reduce the number of detractors.

1. Introduction

Systems for performance measurement often play a key role for companies when developing strategic plans, and when evaluating the achievement of organizational objectives. Traditionally, the companies have almost exclusively relied on financial performance measures, such as EBIT, EBITDA, ROCE, cash flow, etc. However, the understanding of the significance of non-financial information, as well as the use of non-financial performance measurements, such as human capital, brand equity, the customer asset, and environmental performance, as additional valuation tools to the financial performance measurements, has increased over the recent years (Ittner & Larcker, 1998a, 1998b). Organizations have also seen the value of supplementing the financial measures with frameworks with which they are able to study several non-financial performance measures simultaneously. An example of this is the well-known Balanced Scorecard (Kaplan & Norton, 1996; Banker, et al., 2004).

A possible way of assessing the value of the customer asset is through customer satisfaction measurements. In both the industry and academic realm of consumer research, customer loyalty is usually measured in such a survey by a multi-item measurement using some kind of index or a single-item on five or ten point Likert-like scale. One method that has received some attraction the last decade is the concept of Net Promoter Score (NPS), a popular single-item method of loyalty measurement, mainly due to its simplicity. It has its genesis in the original article by Frederick Reichheld ("The one number you need to grow," Harvard Business Review, December 2003). Specifically, the method is to ask the question: "How likely are you to recommend the company to your friend or colleague?" Customers respond to this question on an eleven point Likert-like scale ranging from extremely unlikely (0) to extremely likely (10). Customers are then categorized into promoters, passive, or detractors. Promoters are customers who respond to the question with a 9 or 10. Passive customers are those who rate 7 or 8 on the scale. Detractors are those who respond with 0 through 6. To help organizations achieve a better understanding of the NPS measure, Reichheld further proposed a net promoter score (NPS), which is calculated by subtracting the percentage of detractors from the percentage of promoters, and suggested that NPS should be the only number that companies need to grow because this score has been found to be strongly correlated with the growth rates in many industries (Reichheld, 2003).

The NPS approach is widely diffused and adopted due to its simplicity. But it's strength as a non-financial performance indicators have been criticized since it is unclearing what actually affects the score. The focus of this study, however, is neither to argue whether NPS is a superior metric to other loyalty measures nor to defend NPS as the only number that companies should attend to. Instead, we focus on presenting a method to improve organizations' performances in order to increase the number of promoters and reduce the number of detractors. We use data and the model for customer satisfaction measures developed by EPSI Rating to address to following questions: Can we use customer measures like Image, Expectations, Product Quality, Service and Value for Money to predict if a customer is a detractor, passive or promoters? From a managerial perspective, is it possible to develop a strategy to increase the pool of ambassadors and decrease the pool of detractors? To answer these questions, the study uses an ordinal logistic regression approach for identifying operational elements that drive the transformation of a customer from detractors to promoters. We use customer survey data from EPSI Rating studies within banking, insurance and mobile industry. Both private customers (B2C) and corporate customers (B2B) are covered. The data is from 2016 and from the Swedish operation of EPSI Rating formally known as Svenskt Kvalitetsindex.

2. Conceptual Background

2.1. The short story of NPS

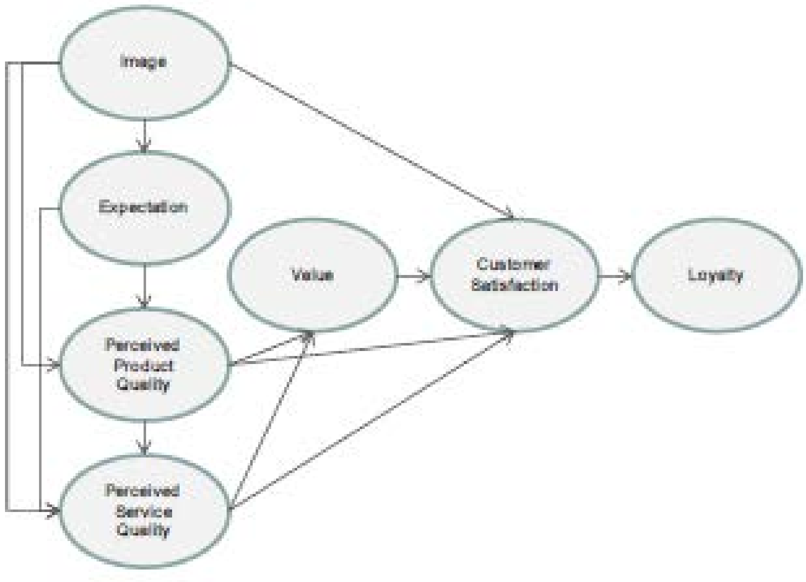
The Net Promoter concept was introduced in a 2003 Harvard Business Review article. One of the claims made by Net Promoter as a metric was the positive relationship with firm revenue growth. The message is that NPS is the single most reliable indicator of a firm's ability to grow. NPS is derived from survey responses to a likelihood to recommend question on an 11-point scale. The proportion of respondents rating the firm a 6 or less (called 'Detractors') is subtracted from the proportion of respondents rating the firm a 9 or 10 (called 'Promoters'); this difference represents a firm's NPS. The reasoning was that people highly likely to recommend a firm were implied as being loyal to the firm and generate profits.

2.2. The EPSI Rating framework

The scope of conducting national customer satisfaction surveys has widened, and since the beginning of the 1990's several countries have developed national indicators measuring customer satisfaction across a wide range of industries, companies and organizations. For example, Sweden was the first nation to establish a national index of customer satisfaction in 1989 (Fornell, 1992); other nations that have developed national indices are, for example, Norway, (Andreassen & Lindestad, 1998), Denmark, (Martensen, et al., 2000), and the US with the American Customer Satisfaction Index (ACSI) (Fornell, et al., 1996). The European Performance Satisfaction Index (EPSI Rating), (ECSI, 1998), conducts annually harmonized customer satisfaction surveys for several industries and in an increasing number of European countries. The EPSI Rating was first initialized by the EC (European Commission) and the Pan-European quality organizations EFQM (European Foundation for Quality Management) and EOQ (European Organization for Quality) in 1997.

The customer experience variables which are in focus in our study are taken from the EPSI-initiative (EPSI, 1998). EPSI Rating (Extended Performance Satisfaction Index) is a system to collect, analyze and disseminate information about image, preferences and perceived quality as well as loyalty of customers, employees and other stakeholders to commercial entities, governmental bodies and other organizations. The EPSI approach focuses on causal analysis derived from structural model elaboration and thorough empirical studies to estimate numerical relationships. A large set of international benchmark databases has been developed since 1999, when the initiative started in a small number of countries.

Figure 1. The EPSI Rating Customer Model



The structural model used by the EPSI Rating for conducting customer satisfaction surveys is presented in Figure 1. The model consists of seven latent variables. The five on the left – Image, Expectation, Product Quality, Service Quality, and Value - are the antecedents of variables on the right-hand side; customer satisfaction and loyalty. The last one, loyalty, being a consequence of customer satisfaction. Each latent variable is measured by multiple manifests. The likelihood to recommend questions (*Rec*) is included as an item in the latent "Loyalty".

2.3. Ordinal Logistic Regression

The dependent variable of this study is of an ordinal categorical type and that needs to be considered in the analysis and that is why ordinal logistic regression is being used. By using ordinal logistic regression technique, we can investigate the impact of say service and product quality across levels of outcomes detractor, passive and promoters. Hence, the investigation can tell us which of the independents, here service- and product quality, have the greater ability in moving customers away from detractors or converting them into promoters. This can be achieved through two version of ordinal logistic regression known as the Proportional Odds Model (PO) and the Partial Proportional Odds Models (PPO).

The PO model, which is also called the cumulative odds model (Agrestic, 1996, 2002, 2010; Ananth & Kleinbaum, 1997; Armstrong & Sloan, 1989; Clogg & Shihadeh, 1994; Liu, 2009; Long, 1997; Long & Freese, 2006, 2014; McCullagh, 1980; McCullagh & Nelder, 1989; Menard, 2010; O'Connell, 2000, 2006; Powers & Xie, 2000; Tutz, 2012), is one of the most commonly used models for the analysis of ordinal categorical data, and it comes from the class of generalized linear models. It is a generalization of a binary logistic regression model when the response variable has more than two ordinal categories. The proportional odds model is used to estimate the odds of being at or below a particular level of the response variable. For example, in our case there are three levels of ordinal outcomes, then the model makes two predictions, each estimating the cumulative probabilities at or below a specific level of the outcome variable. This model can estimate the odds of being beyond a particular level of the response variable as well because below and beyond a particular category are just two opposite directions.

The ordinal logistic regression model can be expressed in the logit form as follows:

$$\ln(Y_j) = logit[\pi(x)] = ln\left(\frac{\pi_j(x)}{1-\pi_j(x)}\right) = \alpha_j + (-\beta_1 X_1 - \cdots - \beta_p X_p) \quad (1)$$

where $\pi_j(x) = \pi(Y \leq j|x_1, \dots, x_p)$, which is the probability of being below at or below a category *j* given a set of predictors, $j = 1, \dots, J-1$. α_j are the cut points and $\beta_1, \dots, \beta_p$ are the logit coefficients. The model predicts cumulative logits across *J-1* response categories. By transforming the cumulative logits, we can obtain the estimated cumulative odds and the cumulative probabilities of being at or below the *j*th category.

The PO model follows the assumption that the effect of each predictor is the same across the categories of the ordinal response variable. In other words, for each predictor, its effect on the ln odds of being at or below any category remains the same within the model. This restriction is referred to as the proportional odds assumption or the parallel lines assumption. To test the parallel-line assumption, a Wald test developed by Brant is usually applied (Brant, 1990). Once the assumption is rejected, alternative models, such as PPO, should be considered (Long & Freese, 2006). The PPO version of (1) is expressed below.

$$\ln(Y_j) = logit[\pi(x)] = ln\left(\frac{\pi_j(x)}{1-\pi_j(x)}\right) = \alpha_j + (-\beta_{1j} X_1 - \cdots - \beta_{pj} X_p) \quad (2)$$

where α_j are the cut points and $\beta_1, \dots, \beta_p$ are the logit coefficients. category.

The general interpretation of the logits are as follows. A positive logit coefficient normally indicates that it is more likely to be in a higher category rather than in a lower category of the outcome variable. To estimate the odds of being at or below a particular category, however, the signs before both the intercepts and logit coefficients in Equation (2) need to be reversed.

3. Data source and descriptive statistics

The data used in this study were collected from EPSI Rating annual customer satisfaction surveys 2016 in Sweden. EPSI Rating measures customer satisfaction in a wider context using structural equation model that has been developed based on components considered crucial for causal analysis (ECSI, 1998).

From the EPSI Rating system, se Figure 1, the following latents from the EPSI model are used as predictor and the outcome

Predictors

- Image
- Customer Expectations (Expect)
- Customer Perceived Product Quality (ProdQ)
- Customer Perceived Service Quality (ServQ)
- Customer Perceived Value (Value)

The dependent variable

- The likelihood to recommend item, from now on called *Rec* within Customer Loyalty defined as
    - Detractors, if *Rec*=1-6.
    - Passives, if *Rec* = 7-8.
    - Ambassador if *Rec*=9-10.
    - Note that the scale differs from the original NPS where detractors are defined as (0-6). The scale in the EPSI customer survey is always between 1-10.

3.1. Descriptive Statistics

The total number of observations is 11 532 that is distributed across six different areas. The collected data comes from three different industries: banking, mobile-and the insurance industry. Every industry is in turn divided into a category for private customers (B2C) and corporate customers (B2B). Descriptive statistics of the dependent variable and independent variables are provided in Table 1 and a graphically in Figure 2.

Table 1. Descriptive statistics

Banking B2C	Mean	Standard Deviation
Image	69.4	22.8
Expect	74.7	22.8
ProdQ	75.2	21.7
ServQ	69.8	22.6
Value	67.0	23.7
Q15b	7.6	2.4

Banking B2B	Mean	Standard Deviation
Image	71.2	20.8
Expect	77.3	21.7
ProdQ	76.1	19.5
ServQ	69.0	21.6
Value	67.2	21.7
Q15b	7.4	2.5

Observations	4394

Observations	3593

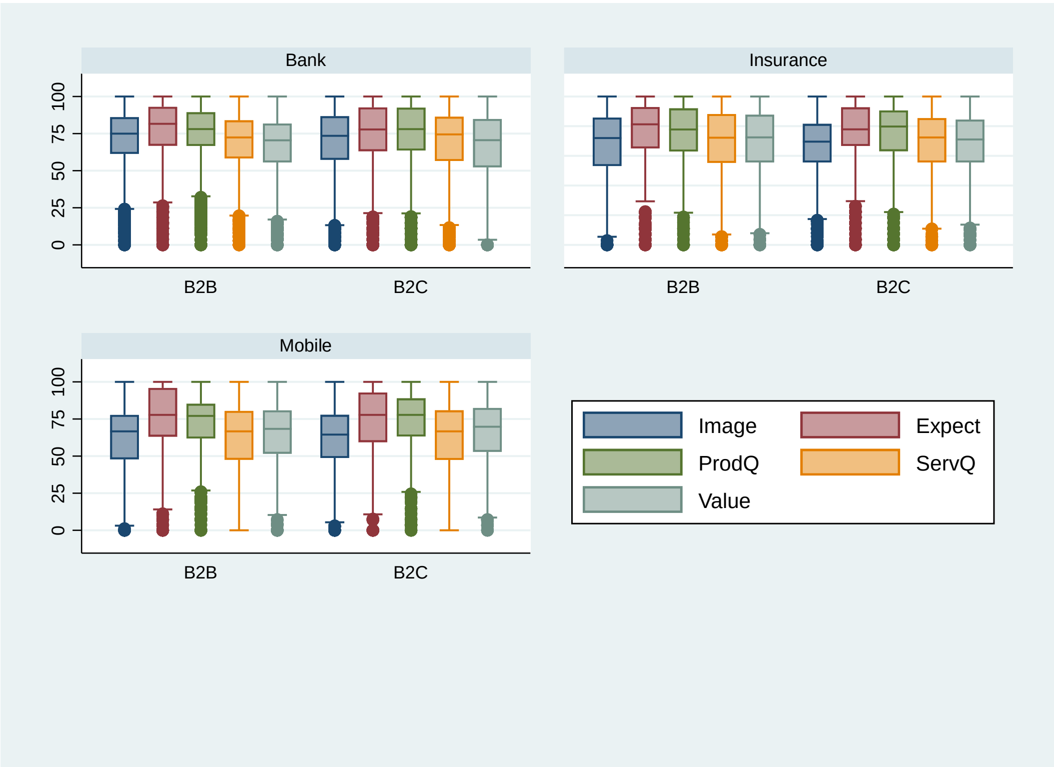
Mobile B2C	Mean	Standard Deviation
Image	62.5	22.3
Expect	73.9	23.5
ProdQ	73.5	21.7
ServQ	63.6	23.2
Value	67.2	21.6
Q15b	7.4	2.4
Observations	1027	

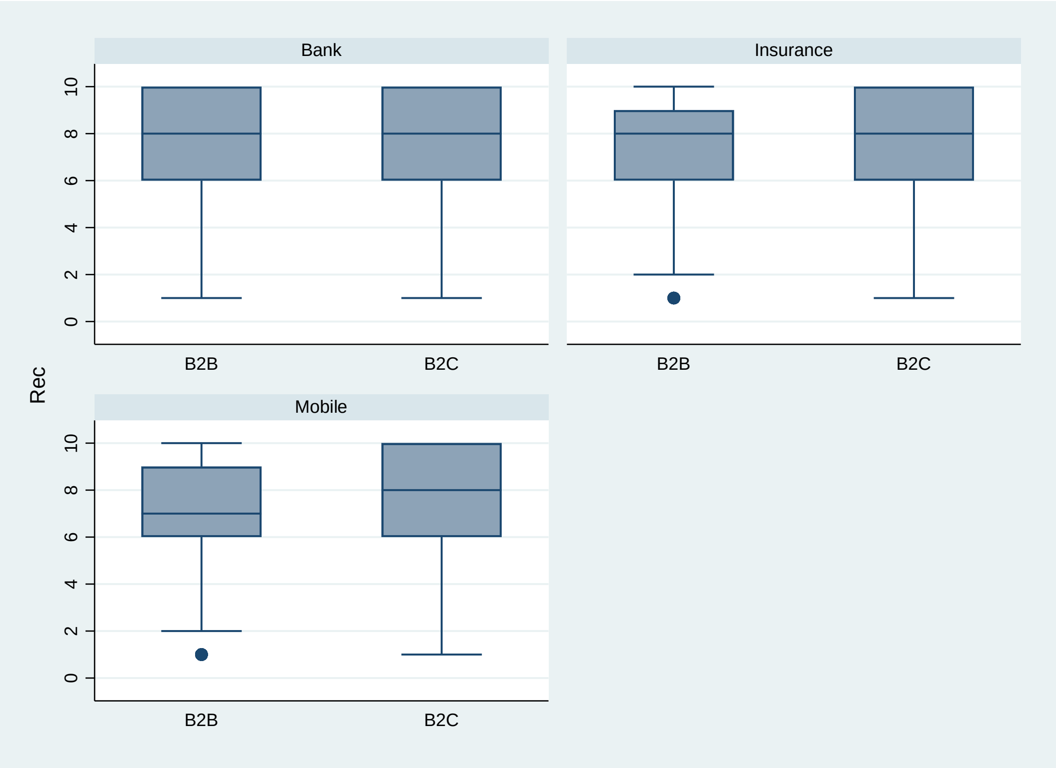
Mobile B2B	Mean	Standard Deviation
Image	62.6	23.5
Expect	74.2	24.5
ProdQ	70.5	22.1
ServQ	63.0	23.7
Value	65.1	22.5
Q15b	7.1	2.2
Observations	767	

Insurance B2C	Mean	Standard Deviation
Image	66.4	22.4
Expect	75.6	23.4
ProdQ	74.8	22.7
ServQ	68.3	22.6
Value	68.5	21.7
Q15b	7.5	2.2
Observations	940	

Insurance B2B	Mean	Standard Deviation
Image	66.8	24.7
Expect	73.9	25.5
ProdQ	72.7	24.6
ServQ	68.2	24.7
Value	69.0	23.5
Q15b	7.5	2.3
Observations	811	

Figure 2. Boxplot




Bank
Insurance
Mobile
Rec
0
2
4
6
8
10
B2B
B2C

4. Results

4.1. Ordinal Logistic Regression

The ordinal logistic regression analysis was conducted to estimate the ordinal outcome variable, that is *Rec*, recommendation class of detractors – passive - promoters, from a set of predictor variables, image, expectations, product quality, service and value for money.

The model estimates for the Proportional Odds Model are presented in Table 2a-2c. The columns correspond to private customers (B2C) and corporate customers (B2B). The estimated coefficients in the model is reported with the related t-value in brackets and some model evaluation statistics in the bottom. Table 2d summarize the odds ratios for each model.

For all models, the LR chi2 tests have low p-values ($p < .001$), which indicated that the model with the five predictors provided a better fit than the null model with no independent variables in predicting the ordinal response variable. The Pseudo R^2 are in general between 0.3 and 0.4, suggesting that the relationship between the response variable, *Rec*, and the five predictors is significant.

By inspection of Table2a-2c it is clear that most of the predictors are significant with a few exceptions. In banking, all predictors are significant for both B2C and B2B. For the insurance data, reported in Table 2b, ProdQ, ServQ and Value are significant for the B2C and ProdQ and Value for B2B. For the mobile B2C, all predictors except expectations are significant and for the B2B only ServQ and Value are significant. Hence, the results indicate that the importance of the five drivers in predicting degree of recommendation differs between segment (B2C and B2C) and industry.

Table 2a. Proportional odds model – Banking

	B2C	B2B
Banking	REC	REC
Image	0.0322***	0.0533***
	(10.91)	(12.61)
Expect	0.00704**	0.00691*
	(2.78)	(2.30)
ProdQ	0.0190***	0.0274***
	(5.37)	(6.28)
ServQ	0.0224***	0.0186***
	(7.11)	(4.72)
Value	0.0399***	0.0493***
	(14.40)	(14.02)
Observations	4394	3593
Pseudo R^2	0.347	0.401
LR chi2	3294.644	3134.215
Prob > chi2	0.000	0.000

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2b. Proportional odds model – Insurance

Insurance	B2C REC	B2B REC
Image	0.0102	0.0151*
	(1.29)	(1.97)
Expect	0.00483	-0.0105
	(0.75)	(-1.55)
ProdQ	0.0284***	0.0287**
	(3.42)	(3.26)
ServQ	0.0300***	0.0134
	(3.81)	(1.79)
Value	0.0581***	0.0685***
	(7.88)	(8.01)
Observations	940	811
Pseudo R^2	0.377	0.363
LR chi2	772.121	643.214
Prob > chi2	0.000	0.000

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 2c. Proportional odds model – Mobile

	B2C	B2B
Mobile	REC	REC
Image	0.0380***	0.0136
	(5.98)	(1.76)
Expect	0.00843	0.00698
	(1.78)	(1.26)
ProdQ	0.0138**	0.00502
	(2.81)	(0.71)
ServQ	0.0144**	0.0185*
	(2.59)	(2.52)
Value	0.0511***	0.0705***
	(8.27)	(8.89)
Observations	1027	767
Pseudo R^2	0.350	0.340
LR chi2	786.426	567.176
Prob > chi2	0.000	0.000

t statistics in parentheses

Table 2d. Odds ratios for the Proportional odds model

	Banking		Insurance		Mobile	
	B2C	B2B	B2C	B2B	B2C	B2B
REC						
Image	1.033***	1.055***	1.010	1.015*	1.039***	1.014
Expect	1.007**	1.007*	1.005	0.990	1.008	1.007
ProdQ	1.019***	1.028***	1.029***	1.029**	1.014**	1.005
ServQ	1.023***	1.019***	1.030***	1.014	1.015**	1.019*
Value	1.041***	1.051***	1.060***	1.071***	1.052***	1.073***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The interpretation of the estimated coefficients is not straightforward in a PO model and therefore we follow the common procedure and transform them to odds ratios as displayed in Table 2d.

We take banking B2C as an example and then the other models can be interpreted in a similar way. For the image predictor, OR = 1.033, which was greater than 1. It indicated that the odds of being above a particular category of *Rec* (higher likelihood to recommend) versus below that category for the *Rec* will increase by 1.033 for a one-unit increase in the predictor image, when holding all the other predictors constant. In general, the value for money predictor gets the highest odds ratios.

In the proportional odds models, we assume that each predictor has the same effects across the categories of the ordinal outcome variable. In other words, the logit regression coefficients for each predictor are the same across the ordinal categories. The estimated logits and the corresponding odds ratios of being at or below category 1, category 2, and category 3 for the predictor, Rec, are assumed to be the same. To test whether the PO assumption is met, we can use the Brant test (Brant, 1990) to look at the logit coefficients of a series of underlying binary logistic regression models for the dichotomized ordinal outcome variable, comparing outcomes at or below a category versus beyond that category.

Table 3. P-values (p>chi2) of the Brant test of parallel regression assumption

	Banking		Insurance		Mobile	
	B2C	B2B	B2C	B2B	B2C	B2B
All	0.000	0.000	0.012	0.059	0.002	0.552
Image	0.155	0.029	0.305	0.096	0.053	0.428
Expect	0.399	0.687	0.014	0.029	0.242	0.743
ProdQ	0.004	0.000	0.104	0.194	0.001	0.217
ServQ	0.837	0.361	0.262	0.934	0.051	0.965
Value	0.979	0.344	0.888	0.029	0.817	0.292

A significant test statistic provides evidence that the parallel regression assumption has been violated.

The results from the Brant test of parallel regression assumption is presented in Table 3. The results are presented as p-values. The overall (All) Brant tests indicates that the proportional odds assumption is violated except for insurance B2C and mobile B2B. By examining the Brant tests for each predictor variable, we find that the proportional odds assumption is mostly violated for ProdQ width some minor difference for the other predictors for specific models.

The partial proportional odds model was fitted to estimate the ordinal outcome variable, *Rec*s, from a set of predictor variables, image, expectations, product quality, service and value for money. This model was used since it allows the effects of some predictor variables to vary when the proportional odds assumption (PO) does not hold. The estimated models are in table 4a-4c with the corresponding odds-ratio in Table 4d.

Table 4a. Partial proportional odds model – Banking

	Banking	
	B2C	B2B
1		
Image	0.0321***	0.0527***
	(10.92)	(12.48)
Expect	0.00706**	0.00732*
	(2.80)	(2.45)
ProdQ	0.0114**	0.0117*
	(2.90)	(2.34)
ServQ	0.0225***	0.0192***
	(7.15)	(4.89)
Value	0.0398***	0.0491***
	(14.39)	(13.98)
2		
Image	0.0321***	0.0527***
	(10.92)	(12.48)
Expect	0.00706**	0.00732*
	(2.80)	(2.45)
ProdQ	0.0283***	0.0452***
	(6.69)	(8.30)
ServQ	0.0225***	0.0192***
	(7.15)	(4.89)
Value	0.0398***	0.0491***
	(14.39)	(13.98)
Observations	4394	3593
Pseudo R^2	0.348	0.405
LR chi2	3312.219	3167.281
Prob > chi2	0.000	0.000

Table 4b Partial proportional odds model – Insurance

	Insurance	
	B2C	B2B
1		
Image	0.0102	0.0291**
	(1.30)	(3.09)
Expect	-0.00490	-0.00990
	(-0.67)	(-1.47)
ProdQ	0.0291***	0.0285**
	(3.50)	(3.22)
ServQ	0.0296***	0.0137
	(3.75)	(1.82)
Value	0.0578***	0.0547***
	(7.81)	(4.98)
2		
Image	0.0102	0.00194
	(1.30)	(0.21)
Expect	0.0181*	-0.00990
	(2.18)	(-1.47)
ProdQ	0.0291***	0.0285**
	(3.50)	(3.22)
ServQ	0.0296***	0.0137
	(3.75)	(1.82)
Value	0.0578***	0.0804***
	(7.81)	(7.60)
Observations	940	811
Pseudo R^2	0.381	0.367
LR chi2	779.205	650.224
Prob > chi2	0.000	0.000

Table 4c. Partial proportional odds model – Mobile

	Mobile	
	B2C	B2B
1		
Image	0.0392***	0.0136
	(6.11)	(1.76)
Expect	0.00852	0.00698
	(1.79)	(1.26)
ProdQ	0.00181	0.00502
	(0.30)	(0.71)
ServQ	0.0197**	0.0185*
	(3.06)	(2.52)
Value	0.0512***	0.0705***
	(8.25)	(8.89)
2		
Image	0.0392***	
	(6.11)	
Expect	0.00852	
	(1.79)	
ProdQ	0.0320***	
	(4.44)	
ServQ	0.00623	
	(0.94)	
Value	0.0512***	
	(8.25)	
Observations	1027	
Pseudo R^2	0.357	
LR chi2	801.996	
Prob > chi2	0.000	

Table 4d. Odds ratios for Partial proportional odds model

	Banking		Insurance		Mobile	
	B2C	B2B	B2C	B2B	B2C	B2B
1						
Image	1.033***	1.054***	1.010	1.030**	1.040***	1.014
Expect	1.007**	1.007*	0.995	0.990	1.009	1.007
ProdQ	1.011**	1.012*	1.030***	1.029**	1.002	1.005
ServQ	1.023***	1.019***	1.030***	1.014	1.020**	1.019*
Value	1.041***	1.050***	1.059***	1.056***	1.053***	1.073***
2						
Image	1.033***	1.054***	1.010	1.002	1.040***	1.014
Expect	1.007**	1.007*	1.018*	0.990	1.009	1.007
ProdQ	1.029***	1.046***	1.030***	1.029**	1.032***	1.005
ServQ	1.023***	1.019***	1.030***	1.014	1.006	1.019*
Value	1.041***	1.050***	1.059***	1.084***	1.053***	1.073***

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The log likelihood ratio chi-square test statistic indicates that the full model with five predictors provided a better fit than the null model with no independent variables in predicting the ordinal response variable. By inspection of Table 4a-4c it is clear that the majority of the predictors are significant with a few exceptions. The interpretation of the model estimation is rather similar to the PO version with some exceptions. The mobile data is used as an example.

The estimated PPO model for mobile is reported in Table 4c. Since the B2B data for mobile does not violet the parallel regression assumption there is only one estimate presented and it is similar to the PO version in Table 2c. For the B2C part it differs since the parallel regression assumption is indeed violated.

The two models, numbered 1, and 2, respectively, compare outcomes being above a particular category relative to being at or below that category. The first model compares categories 2 through 3 with category 1, the second model compares categories 3 with categories 1 and 2.

The ProdQ and ServQ predictors were the only one violating the PO assumption, so its effects varied across the two binary models. Starting with the ProdQ, the estimated logit coefficients were 0.00181 and 0.032 for each respective model. In model 1, t-test = 0.30, $p > 0.05$; and in model 2, t-rest = 4.44, $p < 0.001$. Hence, the ProdQ predictor is not significant in model 1 but in model 2. The two odds ratios are 1.002, and 1.032, respectively. Overall, the odds of being beyond a particular category of Rec increased with the increase in ProdQ. For ServQ it is the other way around with the two odds ratios 1.020 (significant) in model 1 and 1.006 (not-significant) in model 2.

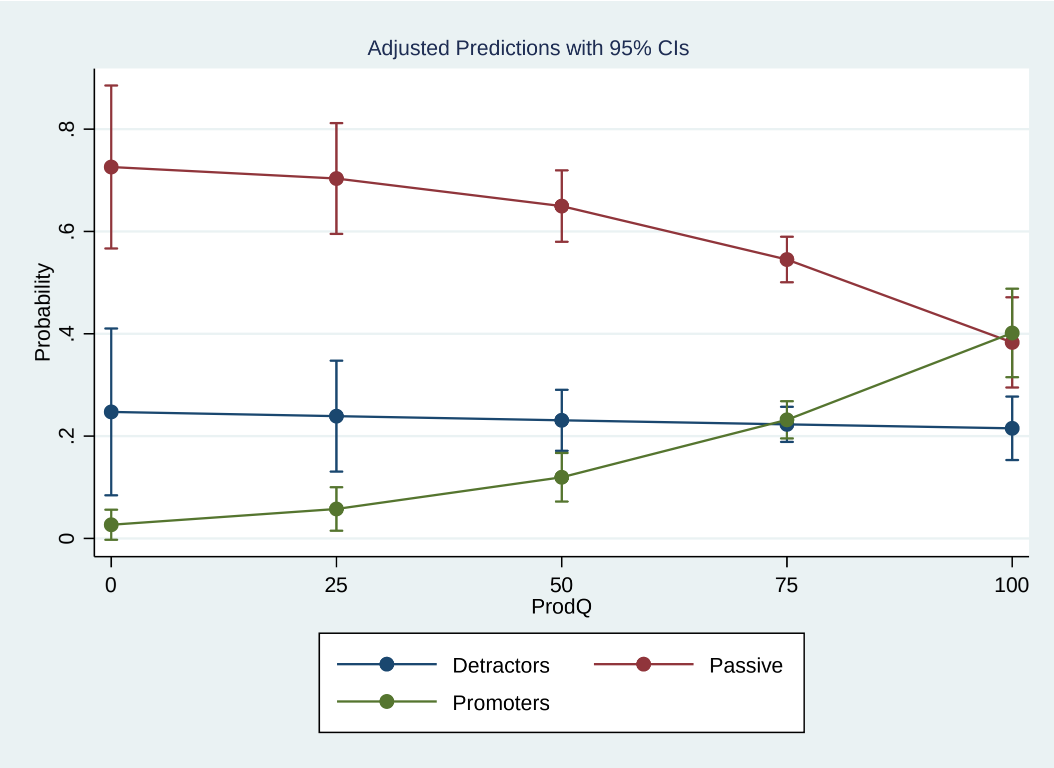
Hence, improving the service quality can significantly increase customers' odds ratios of being promoters or passives versus being detractors. But an improvement in service did not show a significant effect to drive customers to finally become promoters. For the product quality, it is the other way around. Product quality had a significant effect in enlarging the pool of promoters, but the effect of providing product quality was not significant in shrinking the pool of detractors. Table 5 presents a summary of the drivers for each model.

Table 5. A comparison of significant drivers

	Banking		Insurance		Mobile	
Comparison	B2C	B2B	B2C	B2B	B2C	B2B
Decrease the pool of detractors	Value Image Service	Image Value Service	Value ProdQ ServQ	Value Image ProdQ	Image ServQ Value	ServQ Value
Increase the pool of ambassadors	Value Image ProdQ	Image Value ProdQ	Value ProdQ ServQ	Value Image ProdQ	Image ProdQ Value	ServQ Value

This kind of reasoning we do based on Table 5 can also be verified by viewing the results in terms of predicted probabilities at each category of the ordinal response variable for predictor variables at specified values. Figure 3 below present such a graph for mobile B2C when ProdQ takes value of (0, 25, 50, 75, 100) and other predictor variables are held at their means. It shows the predicted probability and the 95 percent confidence interval. It shows that probability of increasing the pool of promoters increases with higher level of product quality and the pool of passive customers is shrinking. Similar charts can be compiled for the other combination of models and data.

Figure 3. Predicted probabilities



5. Conclusion and Discussion

The results of this research offer insights from managerial implications to organizations working with NPS in measuring customer loyalty. The propose model uses the customer perception in terms of image, expectations, product quality, service and value for money as a predictor of the outcome of a customer being a detractor, passive or promoters.

This paper uses an ordinal logistic regression approach and has several advantages over using the conventional method of linear regression models. First, it is more meaningful for companies to know whether certain aspects of customer perception have significant impacts on converting customers to become more loyal i.e., detractors, passive, and promoters). The model takes non-uniform effect into account which is very important from a managerial perspective. This can sharpen organizations' focus by knowing that some of the predictors may have a greater effect on pushing customers away from detractors, and others may have a greater effect on developing customers into promoters. This was found for both banking and mobile data. In the mobile case, it was found that improving the service quality can significantly increase customers' odds ratios of being promoters or passives versus being detractors. But an improvement in service did not show a significant effect to drive customers to finally become promoters. For the product quality, it is the other way around. Product quality had a significant effect in enlarging the pool of promoters, but the effect of providing product quality was not significant in shrinking the pool of detractors.

To improve the NPS score, Reichheld suggested that companies hold direct conversations with detractors and promoters to probe for causes of dissatisfaction and using the customer feedback to build improvement strategies. This kind of studies, however, which are based on a limited sample of customers, cannot generate representative feedback. On the other hand, quantitative analysis in the way this paper proposes based on consumer survey data can generate more reliable results to identify root causes and make optimal customer-oriented decisions. Hence, this paper presents a way to investing if increasing or decreasing aspects of customer perception facets to promote customers to a higher level of loyalty (promoters). This method can be used to facilitate organizations to design a customer improvement strategy.

This paper has some limitations. The study only handles data from Sweden and for certain industries. Hence, it would be interesting to investigate other countries and industries. This is very much possible to do since EPSI Rating are doing surveys on Pan-European level. As mentioned in the introduction, the NPS approach is widely diffused and adopted due to its simplicity. But it's strength as a non-financial performance indicators have been criticized (Kristensen, et al., 2014). It would be interesting to compare other kind of performance measures but that is not the scope for this study but will be addressed in future research.

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