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Count Models: With Applications to Price Plans in Mobile Telecommunication Industry

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Count Models: With Applications to Price Plans in Mobile Telecommunication Industry

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This research assesses the performance of over-dispersed Poisson regression model and negative binomial model with count data. It examines the association between price plan features of mobile phone services and the number of people who adopt the plan. Mobile service data is used to estimate the model with a sample of one million customers running from February 2006 to September 2009. Under three main categories, customer type, age, and handset price, we run the model based on price plan features. Estimates are derived from the maximum likelihood estimation (MLE) method. Root mean squared error (RMSE) is used to observe the statistical fits of all the regression models. Then, we construct four estimation and holdout samples, leaving out one, three, six, and twelve months. The estimation constitutes the in-sample (IS) and the holdout represents the out-sample (OS). By estimating the IS, we predict the OS. Root mean squared error of prediction (RMSEP) is checked to see how accurate the prediction is. Results generally suggest that academic year start (AYS), seasonality, duration of months since launch of price plan (DMLP), basic fees, rate with no discount (RND), free call minutes (FCM), free data (FD), free text messaging (FTM), free perk rating (FPR), and handset support all show significant effect. The significance occurs depending on the segment. The RMSE and RMSEP show that the over-dispersed Poisson model outperforms the negative binomial model. Further implications and limitations of the results are discussed.

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1. Introduction

Mobile wireless service plans offered by major telecommunication firms have been offered to customers since the inception of cell phones. Numerous studies concerning mobile services are devoted to describing pre-tests before service launch or post-tests after the service has been used by customers. For instance, past studies include research on measuring integrity on mobile phone systems (Muthukumaran et al, 2008), adjusting regulation to competition after the Telecommunications Act of 1996 (Shelanski, 2007), switching costs between customer satisfaction and loyalty in mobile phone service (Lee et al., 2001), and generic framework combining semantic web service technology and physical mobile interaction (Broll et al, 2007). In sum, mobile phone service studies in the past are geared towards a security, regulation, psychological, and technological point of view. Research on price-related subjects on mobile phone services has been limited to this point, most likely due to lack of availability of data. Therefore, this study will reveal information that has not been available in past telecommunication research. The following study focuses on competing price plans within a telecommunication firm and evaluates how customers choose between price plan features. We consider this question for categories of customer type, age, and handset price.

The mentioned three main categories are necessary to delve into and investigated before observing price plan features. Customer type is divided into existing customers and new customers. Age is another category that mobile telecommunication industries pay careful attention to as it is directly and indirectly related to income and education level. The way customers react to price plan features is strongly dependent on the age category. For instance, text messaging is more significant to the younger generation and they tend to use it more often than customers in the older age categories. The final important category is handset price. Handset prices can imply which type of cell phone services can be used. For example, a person with a high-priced cell phone will have different options or can receive extra incentives than with someone with a low-priced cell phone. In sum, these three categories need to be separated out and tested upon to look at the specific environment. Each category has different levels and a combination of the levels creates segments.

Given the nature of the data and the fact that the number of people who can adopt a price plan is non-negative integer quantity, the use of count data models is appropriate. Count data models are used extensively in an assortment of fields rationalizing differentiation between instances where it can generate counts such as exposures and events.

In this study, “counts” would have an underlying distribution that is positively or rightly skewed as people initially adopt a plan with high frequency after the launch of a price plan and subsequently the count drops at a constant rate. Therefore, the oft-used linear regression is not appropriate for this case based on its reliance on normal assumption. Also, employing linear regression would result in the expected count to end up with negative predicted values. Logistic regression is not a viable option as well given that counts are not dichotomous choice.

The standard model for count data is the Poisson regression model. Explained in detail by Cameron and Trivedi (1998), this nonlinear regression model is derived from the Poisson distribution by allowing the intensity parameter to depend on covariates. Some of the prominent recent works utilizing Poisson models include studies on cross-category store brand purchase behavior (Wang et al., 2007), patent law expertise with research and development for patenting performance (Somaya et al., 2007), and imitation behavior across new buyers at an online grocery retailer (Choi et al., 2009). However, one of the major flaws of this model is its restrictive assumption of equi-dispersion, where the mean and variance have the same value (Cox, 1983; Dean and Lawless, 1989). If the assumptions are not met, the model will cause the estimates to be inaccurate for the variance terms.

Over-dispersion can be caused by unobserved heterogeneity or excess number of zeros, resulting in an inefficient model (Cameron and Trivedi, 1998). Excess number of zeros can be a problem with a number of people not adopting a particular plan in a given month. To compensate for over-dispersion where the variance exceeds the mean, Breslow (1984) and McCullagh and Nelder (1989) introduced an over-dispersed Poisson model by presenting an extra variation to calculate the inferential statistics.

In the real world, data often includes excess zeros and display over-dispersion. To counter the flaws by Poisson model, negative binomial models are used. They deal with the problem of over-dispersion by assuming that the count variable has a negative binomial distribution, which can be regarded as a generalization of the Poisson distribution with an additional dispersion parameter allowing the variance to exceed the mean (Allison and Waterman, 2002). A random term is introduced to reflect the unexplained between-subject differences included in the regression model (Gardner et al., 1995). Examples include Deb and Trivedi (1997) who conducted research on demand for medical care by the elderly using a finite mixture negative binomial regression. Malyshkina et al. (2009) apply a two-state Markov switching negative binomial model to estimate vehicle accident frequencies in Indiana.

The structure of this research paper is as follows. The next section will introduce the over-dispersed Poisson model and the negative binomial model. Then, the models will be applied to mobile telecommunication service data on each segment. An interpretation of the parameter estimates is provided where we observe trends from the estimates. The RMSE and RMSEP are reviewed to verify which model suits better for this count data. Finally, we discuss implications and limitations for this research.

2. Model Specification

This research takes into account an over-dispersed Poisson model and negative binomial model to analyze the number of people who adopt a price plan. Estimates are calculated via MLE.

Poisson model

Poisson regression is universally used to account for count data in cases of objects, events, and rate. The number of counts approximates a Poisson distribution with the mean λ affected by the regressors and parameters. The Poisson model can be expressed as the condition density function for plan *i* in month *t* by

(1)

$$\Pr(Y_{it} = y_{it} \mid X_{it}) = \frac{\exp(-\lambda_{it})\lambda_{it}^{y_{it}}}{y_{it}!}, \text{ where } \lambda_{it} = \exp(X_{it}\beta_l)$$

and

(2)

$$E(Y_{it} \mid X_{it}, \beta_l, \alpha_g) = \alpha_1 D_1 + \alpha_2 D_2 + \alpha_3 D_3 + \alpha_4 D_4 + \sum X_{it}\beta_l$$

For this application,

$i = 1, \ldots, I$	Index of price plans
$t = 1, \ldots, T$	Index of months
$l = 1, \ldots, L$	Index of independent variables
Y_{it}	Number of counts for price plan i in time t
X_{it}	Values of independent variable for price plan i in time t
λ_{it}	Mean count rate
β_l	Effect of independent variables on mean count rate
α_g	Effect of groups on mean count rate
α_1	Effect of old SMS price plan on mean count rate
α_2	Effect of group price plan on mean count rate
α_3	Effect of current SMS price plan on mean count rate
α_4	Effect of special price plan on mean count rate
D_1	Dummy values for old SMS price plan
D_2	Dummy values for group price plan
D_3	Dummy values for current SMS price plan
D_4	Dummy values for special price plan

Each price plan is clustered into groups depending on characteristics of a plan. For instance, if a particular price plan is only offered to couples, then a dummy value of one is listed in D_2.

The log-likelihood function can be expressed as

(3)

$$LL(\beta_l) = y_{it} \ln \lambda_{it} - \lambda_{it} - \ln(y_{it}!)$$

The MLE of the Poisson regression is calculated via the log-likelihood function in (2). The observed number of people who adopt a price plan have a Poisson distribution.

McCullagh and Nelder (1989)'s method is inputted into the model to offset over-dispersion. They suggest adding a dispersion parameter ϕ in the model along with the mean. The essential problem derives from the fact that variance should equal the mean, but in reality, the variance is larger. Without an over-dispersion parameter, the standard errors of the parameter will be very small. We can test if the dispersion parameter ϕ equals to one. The standard Poisson model assumes ϕ is one. The dispersion parameter equation is

(4)

$$\phi = (I - L)^{-1} \sum_{i=1}^{I} \sum_{t=1}^{T} \frac{(y_{it} - \hat{y}_{it})^2}{V\hat{a}r(y_{it})}$$

This represents the sum of the squared deviation of the actual count from the estimated count and then divided by the estimated variance. The overall sum is divided by the residual degrees of freedom. Including the over-dispersion parameter in the model, the MLE should provide $\phi = 1$ if the standard Poisson model is correct. If $\phi > 1$, we can assume that the data contains over-dispersion.

Negative Binomial

An alternative to the Poisson model is the negative binomial regression. This approach addresses the matter of over-dispersion by adding a random term to the conditional mean of the Poisson model. It is considered a generalization of the Poisson regression and a gamma term is inserted. The density function for plan *i* and month *t* can be defined as

(5)

$$\Pr(Y_{it} = y_{it} \mid X_{it}) = \frac{\Gamma(y_{it} + \alpha^{-1})}{\Gamma(y_{it} + 1)\Gamma(\alpha^{-1})}\left(\frac{\alpha^{-1}}{\alpha^{-1} + \lambda_{it}}\right)^{\alpha^{-1}}\left(\frac{\lambda_{it}}{\alpha^{-1} + \lambda_{it}}\right)^{y_{it}}$$

where

$$\lambda_{it} = \exp(X_{it}B + e_{it}) = \exp(X_{it}B)\exp(e_{it}) \text{ and } \exp(e_{it}) = Gamma(\alpha^{-1}, \alpha^{-1})$$

$$Gamma(\alpha^{-1}, \alpha^{-1}) = \exp(e_{it})^{\alpha^{-1}-1}\frac{\exp(-\exp(e_{it})/\alpha^{-1})}{\Gamma(\alpha^{-1})\alpha^{-1^{\alpha^{-1}}}}$$

Similar to the over-dispersed model, equation (2) applies for the negative binomial model. In the model, if the dispersion parameter α becomes zero, the model collapses to a Poisson distribution, whereas α approaches a large number, the model has a dispersed distribution. The log-likelihood can be expressed as

(6)

$$LL(\beta) = \ln\left(\frac{\Gamma(y_{it} + \alpha^{-1})}{\Gamma(y_{it} + 1)\Gamma(\alpha^{-1})}\right) - (y_{it} + \alpha^{-1})\ln(1 + \alpha\lambda_{it}) + y_{it}\ln(\alpha\lambda_{it})$$

The MLE of the Poisson regression is calculated via the log-likelihood function in (4). The negative binomial is an extended version of the Poisson model with extended variance assumption. However, if the count data contains excess zeros, it may not be suitable, which leads to the next model.

Root mean squared error

RMSE is used to test the difference between the estimates from a model and the actual values observed for the model. It is also useful when the main purpose is to predict the model and see how accurate the model is. We describe respectively *I* as number of plans and *T* as number of months. The following computes the RMSE

(7)

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\frac{1}{I}\sum_{i=1}^{I}(y_{it} - X_{it}B_{l})^{2}}$$

The RMSEP is similar as follows.

(8)

$$RMSEP = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(\frac{1}{I}\sum_{i=1}^{I}(y_{it} - X'_{it}B'_{l})^{2}}$$

X'_{it} Values of independent variable for price plan *i* in time *t* in OS

B'_l Effect of independent variables on mean count rate in IS

We calculate the RMSEP by taking the true value for plan *i* at month *t* in the OS, subtract the prediction, sum them and take the square root. We also compute the RMSEP on a monthly basis for the holdout periods via

(9)

$$RMSEP_{monthly} = \sqrt{\frac{1}{I}\sum_{i=1}^{I}(y_{it} - X'_{it}B'_l)^2}$$

At the estimation stage, with numerous regression results for each model type, we compute an overall RMSE. In the next procedure, we predict the counts holding out one, three, six, and twelve months, and calculate the overall RMSEP and the monthly RMSEP.

3. Methodology

Sample

The sample consists of one million non-US customers who subscribe to price plans. The analysis is viewed from an aggregate level instead of an individual level. Therefore, counts of people who belong in the three main categories are summed up. A sample is dropped if the plan is only eligible to children, teenagers, seniors or handicapped. Additionally, customers who subscribe to standard price plans are not included in the study as it constituted an outlier. The observation period ranges from February 2006 to September 2009 and the data is recorded on a monthly basis. Further, the holdout period for the first OS belongs to September 2009. Hence, we estimate up to August 2009 to predict the counts in September 2009 and see how well it fits. The three month holdout includes July to September 2009 and the six month holdout estimates until April 2009.

Data measures

All measures are collected monthly over the period of February 2006 to September 2009. We describe the measures for various dependent and independent variables.

Dependent Variable

The counts constitute the number of customers who have adopted a plan. It is split up by the three main categories: customer type, age, and handset price. Customer type consists of two levels with existing and new customers. Age is split up into seven levels: under 13, 13-18, 19-24, 25-34, 35-44, 45-60, and 61 and above. Handset prices are divided into three levels: low-, medium-, and high-priced cell phones. All told, there is combination of 42 segments from the $2 \times 7 \times 3$ combination. As mentioned, standard price plans had to be dropped from the dataset as it constituted an outlier with extremely high counts. Under this identification, the number of cases with counts equal to 68,123. However, based on plans eligible to a specific population and the elimination of standard price plans, the number of cases with counts reduces to 55,882. From Figure 1, the histogram resembles a Poisson and negative binomial distribution. Despite the high zero counts, we can still resume using the over-dispersed and negative binomial model.

Independent Variables

The mentioned variables comprise the independent variables that are available in determining the effects of price plans. Basic fees include monthly payment customers must pay for mobile service. RND is the rate for each call without discount after customers exceed the amount they are allowed for basic fees. In other words, it is the rate of the overcharge. Next, FCM, FD, and FTM are incentives for joining a plan on a monthly basis. FCM provides additional voice minutes as an incentive to the original minutes a monthly plan is allowed. FTM is the number of free text messages. FPR is slightly different from incentives in that they provide perks to customers to participate in an "event". FPR is rated on a scale from zero to five with five indicating the best "event". Options in the FPR involve plane tickets, concerts, meal ticket, etc. AYS checks for spikes when school starts. That particular month is coded as 1; otherwise, the variable is marked as 0. Seasonality aspect is inserted to check for other months with spikes, especially holiday season. The log term of seasonality is also taken into account to check for curvilinear relationships. Finally, a dummy variable for old SMS, group, current SMS, and special price plan is introduced if a price plan belongs to one of these four groups. Specifically, old SMS is only offered to ages below 24. Specifics about the details of how they are grouped and what the four represents will not be discussed given its sensitive information.

4. Results

All analysis is done by SAS 9.2. Equations (2), (7), (8), and (9) are programmed and the rest of the equations used formulas available within SAS. Table 1 shows the descriptive statistics and correlations for all the variables. After conducting correlation tests, we removed rates with discounts and night rates as they were both highly correlated with rate with no discounts. The correlations had values of .88 and .94 and were highly significant. These rates are proportional to rates with no discount, only the value of rate is smaller. Initially, rates with discounts and night rates were included in the model, but it caused the model to be unstable, causing estimates to be unreasonable.

In the model estimation step, we model the number of people who adopt a price plan as a function of price plan features for 42 different segments. The segments are a combination of two levels of customer type, seven levels of age group, and three levels of handset prices. Here, we run the over-dispersed Poisson regression and the negative binomial regression on these 42 segments. According to experts in the mobile service industry, observing the effects inside these segments are expected to be very important. We used data February 2006 through September 2009. We estimate the model via maximum likelihood which is straightforward and the default option in SAS. Given the large sample size, maximum likelihood is sufficient to use. The statistical fits of the 42 models is calculated via (7).

Then, we construct an in-sample to predict the holdout period, out-sample, leaving out one month, three months, and six months. Accordingly, the one month holdout essentially means estimating up to August 2009 to predict September 2009 and finally determine how well we predict that OS. The three month and six month calculation is done in similar fashion. We compute the RMSE's for the estimation period as well as the RMSEP's for predicting the OS. An overall RMSEP plus a monthly RMSEP is evaluated.

Results of the estimation with count data

Calculating the RMSE via (7), the over-dispersed Poisson regression and the negative binomial regression RMSE is 697.10 and 840.36. The overall RMSE for the 42 models suggests that the statistical fits for over-dispersed Poisson model are better for explaining the data set than the negative binomial model. Table 2 and Table 3 illustrate the estimates derived from the Poisson and negative binomial model. In terms of interpreting the results, we use the Poisson model for its better fits. Later in the paper, we describe differences in the estimates between the two models and the fits.

In this research, number of people who adopt a price plan, customer adoption, and counts are used interchangeably to define Y_{it}. According to Table 2, interesting patterns emerge observing the trends and specific segments. Table 2 considers significance if the p-value is below .05, highlighted by the gray region. Related to academic year start (AYS), there is significance in five segments within existing customers and two segments within new customers. Observing the former, the estimates with significance occur in the 13 to 18 and 19 to 24 age group except the 13 to 18 with medium-price cell phones. We can see the positive estimates especially in these two age groups, hinting that the number of customers adopting price plans increase for students when the school year starts. For new customers, the below 13 and 13 to 18 age groups with medium-priced cell phones show significance. Both have positive estimates as number of customers increase for these two age groups.

Examining seasonality and the log of seasonality show obvious difference between existing and new customers with more significance occurring in the former. In terms of interpreting seasonality and the log of it, if the former is negative and the latter is positive, the number of customers who adopt a plan depicts a U-shaped picture. In other words, counts are high in the early part of the year and that number decreases in mid-season and then steadily increases approaching the end of the year. On the other hand, if the former is positive and the latter is negative, we get an inverted U-shaped pattern for counts, implying that the number of customers who adopt a plan peaks in the middle of the year. Among existing customers, the below 13 age group with low- and medium-priced cell phones show significance. The below 13 and low-priced cell phone segment displays a U-shaped pattern. The below 13 and medium-priced cell phone segment is only significant for the log term where counts increase rapidly along the year and settles toward the end. In the middle of the table for existing customers, there are six segments with significance, all displaying an inverted U-shaped trend for counts. The new customer section displays significance across the board in nearly every segment by portraying an inverted U-shaped pattern. However, the 13 to 18 age group with high-priced cell phone segment presents a positive linear increase along the year.

Examining existing customers in the basic fees, the effect of price has significant results on number of customers who adopt a plan. One fascinating trend is noticeable in existing customers. While the overall basic fee has a negative effect on counts, the segments with high-priced cell phones suggest that increasing basic fees, in general, will increase customer adoption. Plus, this pattern also happens with medium-priced cell phones in the 35 to 44 and 45 to 60 age groups. Contrary to existing customers, new customers react differently to basic fees. The below 13 and 13 to 18 age groups have positive effects.

This can be attributed to the fact that the parents are in charge of their invoice. In result, the rest of the age groups all show negative effect on number of customers who adopt a plan. The one segment that did not show significance is the 35 to 45 age group with high-priced cell phones.

The rate with no discount (RND) is the overcharge paid by customers if they exceed the amount allotted for their basic fees. The trend follows the same script as basic fees for new customers. For both existing and new customers, the below 13 and 13 to 18 age groups have positive effects on customer adoption, whereas the other age groups display negative effects. Hence, negative estimates suggest that the increase in rate with no discount will decrease the number of people who adopt a price plan. The reason for the positive estimates in the below 13 and 13 to 18 age groups follow the same rationale as parents take charge of the bill.

It is hard to capture the trend inside free call minutes (FCM) other than the fact that negative and positive estimates appear sporadically across segments. For existing customers, the 19 to 24, 35 to 44, and 45 to 60 age groups can be seen as showing indifference to free call minutes offered by the mobile service. Yet, the 25 to 34 and 61 and above age groups contains positive estimates. We can imply that free call minutes for a price plan heavily depends on which age group a customer belongs to. In the new customer category, other than below 13 and 13 to 18 age groups, the rest of the age groups have a positive effect on number of customers who adopt a price plan. Interestingly, the 35 to 44 age group with high-priced cell phones is unresponsive to this free incentive.

One trend can be noticed for free text message (FTM) variable in both new and existing customers. The 13 to 18 and 19 to 24 age groups are presented with positive estimates with significance. These two age groups respond to free text messages with an increase in customer adoption. The rest of the age groups are not concerned with free text messages. However, three segments for new customers react positively to this variable. Those are 35 to 44 age group with high-priced, 45 to 60 with medium-priced, and 61 and above with high-priced cell phones.

The free perk rating (FPR) display different viewpoints for existing and new customers. Among existing customers, in general, free perk rating show positive estimates except for segments containing low-priced cell phones. In spite of this, the 61 and above age group with low-priced cell phones take the free perks and this incentive increases the count. For new customers, most of the segments have a positive effect on counts.

The old SMS is provided only for customers with ages below 24. Therefore, the rest of the segments contain a N/A mark in the table. In sum, the 19 to 24 age group show positive estimates in existing and new customers, while the rest of the age groups have negative estimates. The group price plan all exhibit positive effects on counts. In general, the current SMS price plans show positive estimates as well. Oddly, in the new customer category, the 19 to 24 age group with and low-priced cell phone segment holds a negative estimate. On behalf of special price plans, all estimates are positive apart from a few segments. For both existing and new customers, the 19 to 24 age group who carry low- and medium-priced cell phones are presented with negative effects. Additionally, in the new customer category with the same pattern, the 25 to 34 age group is negative.

Finally, the scale parameter all exceed one, confirming that over-dispersion exists in the mobile service dataset.

Comparison to negative binomial model

Table 3 lists the parameter estimates for the 42 segments for the negative binomial model. Similar to over-dispersed Poisson model, the gray region displays significant effects with p-values less than .05. Looking at the relationship between price plan features and number of customers who adopt a price plan, the evaluation of the two models estimated via MLE method shows a lack of consistency between the two model in terms of significance regions and estimate values. First, one of the obvious observations is that none of the academic year start variable for the negative binomial model is significant. In addition, this occurs for seasonality in existing customers. Taking a closer look at basic fees in both models, the parameter values are not remotely close. Also, the segment containing existing customers, 61 and above age, and medium-priced cell phones, the algebraic signs are the opposite. The Poisson model has a negative value, whereas the negative binomial model has a positive. Second, the over-dispersed Poisson model seems to have a high scale parameter for the segment encompassing existing customer, 25 to 34, and medium-priced cell phones. However, the dispersion parameter for the negative binomial model is high in the new customer, 61 and above age group, high-priced cell phone segment. Third, as mentioned, based on RMSE values, the over-dispersed Poisson model performs better than the negative binomial model. The RMSEP and the monthly RMSEP will be further dealt in the next section.

Results of the holdout sample

From Table 4, we look at the statistical fits to see how well the in-sample (IS) predicts the out-sample (OS). A one month IS would indicate calculating the RMSE from February 2006 to August 2009. The one month OS computes the RMSEP to see the statistical fits from using the IS to predict the OS. The IS do not show much fluctuation for the Poisson model. The negative binomial model's RMSE increase removing the last year of the data with a value of 943.288. The RMSEP for the OS indicates that the Poisson model outperforms the negative binomial model. For the negative binomial, for every increase in predicting months ahead, the RMSEP performs worse.

For Table 5, the monthly RMSEP performs better for the over-dispersed Poisson model. For 3 months and 6 months OS, the RMSEP value increases for every next month. In the 12 months column for both models, the RMSEP increases in November, December, and January, then the value drops. There seems to be an unexpected situation or condition that makes the expected number of people who adopt a price plan different from our count data.

5. Implications and Limitations

The goal of this research is to address two issues: (1) What are the effects of price plan features on number of people who adopt a price plan segmented by customer type, age, and handset price? and (2) How well can we predict future counts taking into account the previous estimates? Results suggest that price plan features, in general, have a significant effect on counts and that aspect greatly depends on segment. To account for this unique model setup, the over-dispersed Poisson regression and negative binomial regression model with aggregated count data is applied. Dataset on mobile service plans have not been available to this point and this research provides a unique perspective on telecommunication studies.

Creating the segments from the three categories is crucial to run the model. What occurs inside these segments are paid special attention to by the mobile service industry. Therefore, they are separated out instead of used as part of the regressor. The segments yield 42 models and the study is run from February 2006 to September 2009 with one million customers. We are able to identify a mixture of time-varying variables, cost, and incentives that factor into the number of customers who adopt a price plan.

The paper has its limitations as well. First, for some of the price plans, the expected counts were not close to the actual counts with constant underestimation. Those price plans have exceptionally high counts that are not explained by our model. Additionally, it would have been ideal to include the standard price plans. Including the standard plans yielded estimates that make sense, but the overall RMSE increased to a five digit range.

Second, the data available does not contain variables related to sales marketing at local mobile stores and internet and television exposure, which can account for sudden increases in counts. Data on sales marketing and advertising exposure is not open for researchers to apply. When the count increases, the model did not predict accurately for a price plan as this issue is also related to the first limitation. Local mobile stores receive incentives from headquarters for selling a particular price plan and they would heavily push a price plan to customers for their own sake. Then, the counts would suddenly increase at a high rate during a season. That may be one of the explanations for the high RMSEP in November and December 2008 and January 2009. In addition, customers may view advertisements on price plans from an internet or television source.

Finally, the model itself may not explain the data. More suitable options can include the zero-inflated model or the finite mixture model with latent classes. The zero-inflated model can have two sets of predictors, one set is used to predict zero values and one is used to predict counts as well as zero values. The model can predict a zero value that is generated from one of the two populations (Simons et al., 2006). A mixture model can capture the tails better than the Poisson and negative binomial model. Instead of the experimenter assigning plans to a group, it would be more informative for the price plan to identify classes of objects that differ in the parameters of the model (Wedel et al., 1993). Future research needs to address these issues.

Table 1
Descriptive Statistics and Correlation Coefficients

	M	Std. Dev.	1 count	2 AYS	3 seas	4 log(seas)	5 basic fees	6 RND	7 FCM	8 FTM	9 FPR	10 old SMS	11 group	12 Curr. SMS
1 count	384.48	1292.00												
2 AYS	0.09	0.28	0.0018											
3 seas	6.41	3.26	-0.0028	-0.32***										
4 log(seas)	1.67	0.68	-0.0037	-0.26***	0.94***									
5 basic fees	29.48	20.48	-0.034***	-0.014***	0.016***	0.024***								
6 RND	19.56	4.12	0.086***	0.0096**	-0.011***	-0.019***	-0.50***							
7 FCM	240.39	293.73	-0.024***	-0.011***	0.013***	0.014***	0.81***	-0.39***						
8 FTM	312.40	586.17	0.033***	-0.0048	-0.006	-0.0021	0.0055	0.27***	0.15***					
9 FPR	2.65	1.94	0.051***	-0.018***	-0.0018***	0.0051	-0.040***	-0.088***	0.076***	0.22***				
10 old SMS	0.02	0.13	0.096***	0.0021	0.00034	0.00058	-0.021***	0.32***	-0.054***	0.65***	0.051***			
11 group	0.22	0.41	-0.13***	0.0015	0.0057	0.0036	-0.14***	0.018***	-0.15***	-0.16***	-0.079***	-0.067***		
12 curr. SMS	0.40	0.49	-0.11***	0.0018	-0.0074*	-0.0076*	0.19***	-0.22***	0.13***	0.067***	-0.079***	-0.10***	-0.42***	
13 special	0.22	0.42	0.059***	0.0078*	-0.0070*	-0.0070*	-0.061***	-0.11***	0.00075	0.011***	0.20***	-0.069***	-0.28***	-0.43***

* $p < .10$
** $p < .05$
*** $p < .01$

Table 2
Results of over-dispersed Poisson Regression on Count Data

cust. type	age	cell price	intercept	AYS	seas	log(seas)	basic fees	RND	FCM	FTM	FPR	old SMS	group	curr. SMS	special	Scale
existing	below 13	low	13.086	-0.023	-0.047	0.323	-1.215	0.106	0.000	-0.002	-0.108	-4.655	3.700	1.978	1.242	10.019
existing	below 13	medium	9.862	-0.017	-0.033	0.288	-1.047	0.114	0.001	-0.002	0.079	-4.574	4.546	2.480	1.540	14.364
existing	below 13	high	-8.054	-0.185	0.016	-0.005	0.248	0.098	0.000	-0.001	0.184	-1.699	3.897	2.431	1.746	3.734
existing	13 to 18	low	6.461	0.144	-0.016	-0.009	-0.817	0.104	-0.001	-0.001	0.045	-3.275	4.711	2.424	2.165	14.821
existing	13 to 18	medium	8.532	0.093	-0.008	-0.007	-0.985	0.104	0.000	-0.001	0.106	-3.648	5.049	2.732	2.174	26.579
existing	13 to 18	high	-3.435	0.174	0.015	-0.014	-0.200	0.111	0.000	-0.001	0.181	-2.480	4.879	2.556	2.016	6.675
existing	19 to 24	low	21.269	0.161	0.022	-0.090	-1.451	-0.132	-0.001	0.001	-0.151	1.929	1.200	0.190	-0.992	21.151
existing	19 to 24	medium	13.660	0.180	0.059	-0.240	-0.775	-0.131	-0.001	0.001	0.057	1.818	2.033	0.957	-0.115	33.035
existing	19 to 24	high	-0.474	0.153	0.057	-0.223	-0.013	-0.134	-0.001	0.001	0.374	2.481	3.296	1.980	1.154	13.009
existing	25 to 34	low	13.685	0.014	0.029	-0.179	-0.943	0.021	0.001	0.000	-0.072	N/A	2.155	1.129	-0.029	26.809
existing	25 to 34	medium	8.120	0.016	0.040	-0.216	-0.402	-0.002	0.000	0.000	0.129	N/A	2.754	1.562	0.469	33.656
existing	25 to 34	high	-3.091	0.102	0.041	-0.200	0.275	-0.050	0.000	0.000	0.401	N/A	3.935	2.362	1.475	14.146
existing	35 to 44	low	9.491	-0.025	0.032	-0.200	-0.446	-0.125	-0.001	-0.001	-0.076	N/A	3.163	1.498	0.850	20.724
existing	35 to 44	medium	1.901	-0.054	0.031	-0.148	0.162	-0.088	-0.001	-0.001	0.098	N/A	3.683	1.881	1.219	22.955
existing	35 to 44	high	-7.906	0.051	0.022	-0.084	0.636	-0.060	0.000	-0.002	0.284	N/A	4.546	2.325	1.827	9.107
existing	45 to 60	low	7.633	-0.032	0.025	-0.169	-0.421	-0.062	-0.001	-0.001	-0.053	N/A	3.168	1.680	0.878	18.131
existing	45 to 60	medium	0.128	-0.035	0.038	-0.179	0.201	-0.033	-0.001	-0.001	0.121	N/A	3.646	2.068	1.243	20.588
existing	45 to 60	high	-8.868	0.052	0.041	-0.172	0.639	-0.031	-0.001	-0.001	0.290	N/A	4.438	2.489	1.784	7.556
existing	61 and above	low	13.111	0.042	0.030	-0.199	-1.404	-0.007	0.001	-0.001	0.036	N/A	3.650	2.326	1.371	10.290
existing	61 and above	medium	4.895	0.006	0.006	-0.043	-0.524	-0.032	0.000	-0.001	0.178	N/A	3.914	2.300	1.428	11.237
existing	61 and above	high	-10.759	-0.003	0.015	-0.077	0.711	-0.023	0.000	-0.001	0.279	N/A	3.965	2.474	1.717	4.811

(continued)

(Table 2 continued)

new	below 13	low	-4.696	0.143	-0.256	1.032	0.628	0.244	-0.003	-0.002	0.000	-7.438	3.456	-0.112	0.951	10.898
new	below 13	medium	1.911	0.302	-0.057	0.234	-0.057	0.223	-0.001	-0.003	0.167	-8.093	3.739	0.899	1.202	6.997
new	below 13	high	-34.516	0.234	-0.217	1.494	0.670	0.226	-0.001	-0.002	0.331	-5.699	N/A	1.182	1.369	2.533
new	13 to 18	low	-16.436	0.106	-0.195	0.582	1.325	0.283	-0.004	-0.001	0.261	-5.045	4.396	0.213	1.675	17.806
new	13 to 18	medium	-8.180	0.229	-0.016	-0.094	0.873	0.192	-0.001	-0.002	0.009	-5.977	4.045	1.337	1.499	13.765
new	13 to 18	high	-17.176	0.051	0.082	0.002	1.250	0.170	-0.002	-0.002	-0.021	-5.859	5.875	1.301	1.763	4.141
new	19 to 24	low	26.606	0.134	-0.219	0.686	-2.093	-0.031	0.000	0.001	0.009	-0.470	0.741	-0.772	-1.633	11.403
new	19 to 24	medium	23.270	0.081	-0.020	-0.049	-1.867	-0.071	0.001	0.001	0.103	0.796	1.195	0.103	-1.000	12.957
new	19 to 24	high	6.670	-0.147	-0.057	0.294	-1.140	-0.081	0.000	0.001	0.518	2.975	3.142	1.367	0.271	5.500
new	25 to 34	low	26.923	0.155	-0.182	0.685	-2.228	-0.036	0.002	0.000	0.043	N/A	0.924	-0.115	-0.967	13.517
new	25 to 34	medium	20.461	0.014	-0.072	0.219	-1.670	-0.020	0.002	0.000	0.148	N/A	1.461	0.651	-0.441	13.859
new	25 to 34	high	11.222	-0.260	-0.233	1.085	-1.211	-0.120	0.001	0.001	0.457	N/A	3.113	1.741	0.659	6.578
new	35 to 44	low	20.806	0.013	-0.194	0.736	-1.420	-0.209	0.000	-0.001	0.032	N/A	1.572	0.145	0.036	11.417
new	35 to 44	medium	10.812	-0.038	-0.088	0.287	-0.680	-0.127	0.000	-0.001	0.077	N/A	2.345	1.028	0.525	8.989
new	35 to 44	high	1.117	-0.146	-0.254	1.343	-0.162	-0.168	-0.001	0.000	0.207	N/A	3.253	1.507	1.212	4.084
new	45 to 60	low	18.839	0.096	-0.187	0.681	-1.370	-0.164	0.000	-0.001	0.039	N/A	1.870	0.359	0.163	10.342
new	45 to 60	medium	12.088	-0.050	-0.113	0.449	-0.881	-0.111	0.000	0.000	0.111	N/A	2.359	1.074	0.397	8.449
new	45 to 60	high	2.524	-0.048	-0.177	0.920	-0.431	-0.136	0.000	0.000	0.249	N/A	3.765	1.607	0.962	3.715
new	61 and above	low	27.570	-0.037	-0.064	-0.016	-2.480	-0.226	0.001	-0.001	0.118	N/A	2.752	1.263	1.071	6.336
new	61 and above	medium	15.283	-0.230	-0.177	0.692	-1.767	-0.028	0.001	-0.001	0.267	N/A	3.330	1.886	1.360	6.324
new	61 and above	high	0.147	0.319	-0.266	1.542	-0.460	-0.099	0.000	0.000	0.231	N/A	3.687	1.755	1.257	2.664

Gray region is significant at .05 level

Table 3
Results of Negative Binomial Regression on Count Data

cust. type	age	cell price	intercept	AYS	seas	log(seas)	basic fees	RND	FCM	FTM	FPR	old SMS	group	curr. SMS	special	Scale
existing	below 13	low	6.398	-0.021	0.040	-0.073	-0.452	0.158	0.000	-0.002	-0.005	-5.823	3.943	1.376	0.680	4.127
existing	below 13	medium	-4.810	-0.047	0.059	-0.196	0.168	0.168	0.000	-0.002	0.191	-3.050	4.965	2.196	1.414	2.472
existing	below 13	high	-24.189	-0.515	0.057	-0.323	1.505	0.083	-0.003	0.000	0.276	0.823	4.420	3.416	2.515	7.290
existing	13 to 18	low	9.780	0.052	0.037	-0.157	-1.067	0.156	0.000	-0.001	-0.005	-3.389	4.296	1.385	1.070	3.856
existing	13 to 18	medium	0.904	-0.167	0.051	-0.163	-0.576	0.168	0.000	0.000	0.171	-1.124	5.042	2.160	1.757	2.232
existing	13 to 18	high	-15.930	0.227	0.059	-0.396	0.559	0.065	-0.002	0.001	0.133	2.320	5.173	3.532	2.703	4.910
existing	19 to 24	low	25.042	0.157	0.049	-0.270	-1.525	-0.094	0.000	0.000	-0.067	-0.591	0.678	-0.571	-1.468	1.953
existing	19 to 24	medium	15.587	0.132	0.054	-0.281	-0.845	-0.113	-0.001	0.000	0.162	0.802	1.741	0.491	-0.339	1.428
existing	19 to 24	high	2.987	0.086	0.024	-0.209	-0.117	-0.131	-0.001	0.000	0.380	1.562	2.805	1.232	0.648	1.660
existing	25 to 34	low	16.900	-0.021	0.031	-0.206	-1.317	0.095	0.002	-0.001	-0.041	N/A	2.082	0.446	-0.655	1.577
existing	25 to 34	medium	7.442	-0.038	0.052	-0.301	-0.516	0.089	0.001	-0.001	0.173	N/A	2.990	1.393	0.306	1.077
existing	25 to 34	high	-4.338	-0.092	0.001	-0.095	0.290	0.035	0.000	-0.001	0.382	N/A	3.956	2.081	1.178	1.089
existing	35 to 44	low	-1.164	-0.093	-0.010	0.014	0.129	0.104	0.000	-0.002	0.035	N/A	3.654	1.323	0.778	1.593
existing	35 to 44	medium	-10.209	-0.097	0.033	-0.173	0.863	0.124	0.000	-0.002	0.189	N/A	4.403	2.004	1.426	1.083
existing	35 to 44	high	-17.450	-0.024	-0.014	0.019	1.280	0.073	-0.001	-0.001	0.316	N/A	4.988	2.345	1.991	1.603
existing	45 to 60	low	0.280	-0.099	0.012	-0.114	-0.045	0.120	0.000	-0.001	0.022	N/A	3.518	1.407	0.679	1.495
existing	45 to 60	medium	-5.991	-0.059	0.046	-0.224	0.478	0.122	0.000	-0.001	0.152	N/A	4.077	2.010	1.202	1.028
existing	45 to 60	high	-16.841	-0.192	-0.012	0.030	1.107	0.124	-0.001	-0.001	0.274	N/A	4.947	2.478	1.808	1.484
existing	61 and above	low	-1.751	-0.015	0.023	-0.168	-0.206	0.130	0.001	-0.002	0.017	N/A	4.189	2.332	1.475	2.531
existing	61 and above	medium	-7.813	-0.039	0.028	-0.150	0.379	0.126	0.000	-0.001	0.176	N/A	4.496	2.449	1.608	1.484
existing	61 and above	high	-15.421	-0.096	0.062	-0.406	1.001	0.064	-0.001	-0.001	0.309	N/A	4.312	2.451	1.732	3.280

(continued)

(Table 3 continued)

new	below 13	low	17.575	0.048	-0.225	0.806	-1.172	0.270	0.001	-0.003	0.050	-10.645	3.014	-0.679	-0.604	13.541
new	below 13	medium	-2.446	0.145	0.015	-0.112	0.113	0.236	-0.001	-0.002	0.304	-5.930	3.958	1.027	0.913	7.284
new	below 13	high	-28.669	-0.406	-0.485	2.654	0.384	0.324	0.001	-0.004	0.591	-10.501	N/A	1.119	0.343	15.036
new	13 to 18	low	17.966	0.322	-0.048	0.210	-1.491	0.343	0.000	-0.002	0.032	-8.708	3.294	-1.611	-1.241	13.443
new	13 to 18	medium	2.914	0.208	0.012	-0.164	-0.763	0.258	0.000	0.000	0.234	-2.251	3.843	0.861	0.745	6.263
new	13 to 18	high	-16.374	0.076	0.140	-0.385	0.492	0.297	0.000	-0.001	0.312	-2.012	5.863	0.503	1.275	12.754
new	19 to 24	low	38.383	0.121	-0.188	0.457	-2.827	-0.019	0.002	0.000	-0.148	-2.947	0.181	-1.760	-2.440	6.812
new	19 to 24	medium	20.366	-0.090	-0.062	0.053	-1.607	-0.072	0.001	0.001	0.139	1.049	1.392	0.065	-0.890	2.012
new	19 to 24	high	6.393	-0.200	-0.119	0.504	-0.882	-0.104	0.000	0.001	0.409	2.476	2.743	0.785	0.137	4.877
new	25 to 34	low	36.283	0.183	-0.162	0.620	-3.131	0.020	0.004	-0.002	-0.059	N/A	0.841	-0.993	-1.910	5.060
new	25 to 34	medium	24.200	-0.080	-0.075	0.198	-2.029	-0.035	0.003	-0.001	0.185	N/A	1.801	0.465	-0.605	1.519
new	25 to 34	high	8.185	0.021	-0.051	0.228	-0.991	-0.024	0.002	0.000	0.433	N/A	3.218	1.120	0.305	3.724
new	35 to 44	low	22.938	0.035	-0.142	0.504	-1.812	-0.058	0.001	-0.002	0.017	N/A	1.632	-0.494	-0.874	5.297
new	35 to 44	medium	9.657	-0.075	-0.062	0.182	-0.796	-0.011	0.001	-0.001	0.144	N/A	2.644	0.784	0.261	1.817
new	35 to 44	high	1.533	0.019	-0.097	0.709	-0.208	-0.163	0.000	-0.001	0.235	N/A	3.210	1.398	1.043	7.515
new	45 to 60	low	16.001	0.093	-0.212	0.779	-1.410	0.039	0.001	-0.001	0.026	N/A	2.163	-0.100	-0.506	5.559
new	45 to 60	medium	10.072	-0.137	-0.114	0.516	-0.908	0.000	0.001	-0.001	0.142	N/A	2.607	0.901	0.207	2.006
new	45 to 60	high	-5.675	-0.396	-0.171	0.933	0.094	0.026	0.000	0.000	0.212	N/A	3.959	1.552	0.822	8.044
new	61 and above	low	25.423	-0.375	-0.204	0.655	-2.217	-0.183	0.001	-0.001	0.026	N/A	2.513	0.803	0.278	14.553
new	61 and above	medium	2.388	-0.194	-0.078	0.363	-0.717	0.126	0.001	-0.002	0.178	N/A	3.877	1.504	1.025	5.573
new	61 and above	high	-17.024	-0.091	-0.146	0.940	0.802	0.095	0.000	-0.001	0.362	N/A	4.428	2.088	1.310	24.539

Gray region is significant at .05 level

Table 4

RMSE and RMSEP for Over-dispersed Poisson and Negative Binomial Model

	over-dispersed Poisson model	negativebinomial model
1 month IS	689.939	835.757
3 months IS	677.122	830.408
6 months IS	671.099	845.465
12 months IS	665.190	943.288
1 month OS	992.681	1206.267
3 months OS	1007.493	1217.154
6 months OS	995.549	1309.587
12 months OS	1036.109	2091.868

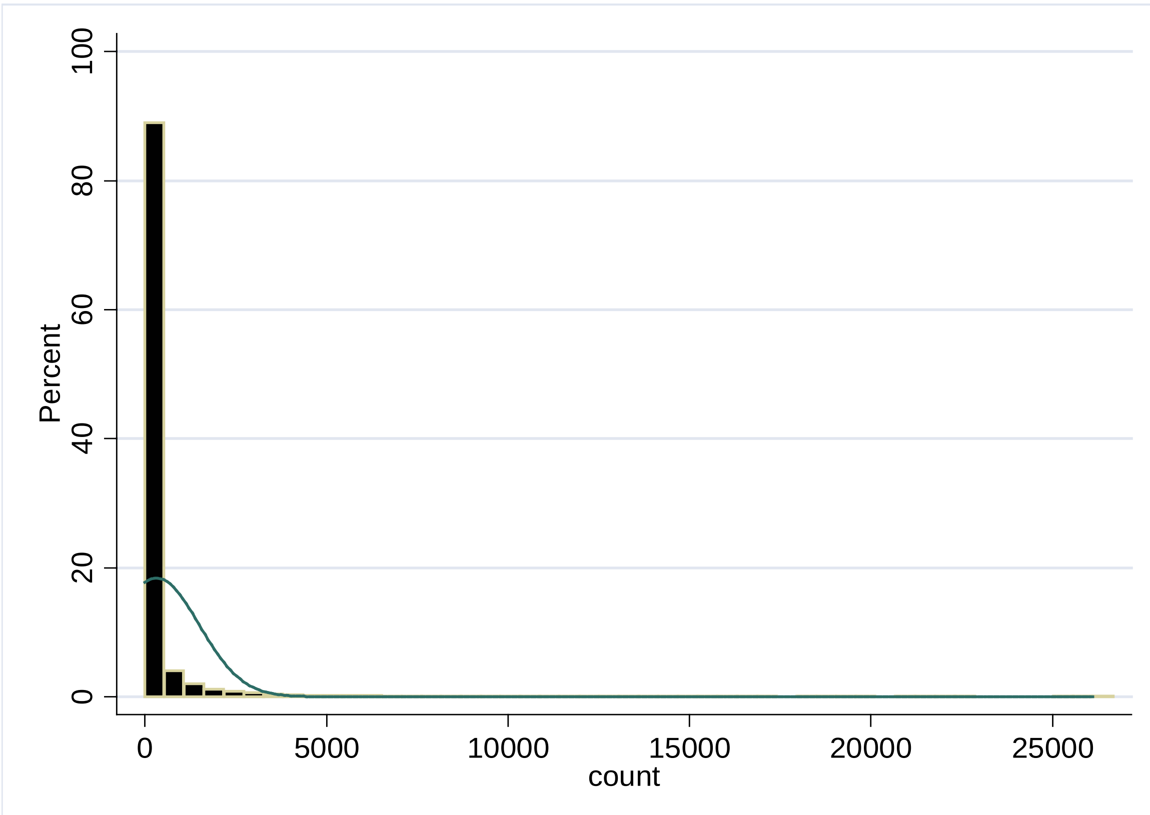
Table 5

Monthly RMSEP for Over-dispersed Poisson and Negative Binomial Model

	over-dispersed Poisson model				negative binomial model			
	1 month OS	3 months OS	6 months OS	12 months OS	1 month OS	3 months OS	6 months OS	12 months OS
2008/10				707.040				1681.724
2008/11				763.521				1940.136
2008/12				889.149				2199.899
2009/01				1046.737				2558.213
2009/02				927.707				2177.283
2009/03				918.599				1818.734
2009/04			725.090	822.402			1153.687	1880.913
2009/05			731.099	823.926			1137.042	1840.405
2009/06			980.806	1170.390			1281.664	2120.978
2009/07		883.339	1038.408	1233.002		1084.341	1306.065	2142.986
2009/08		1042.262	1176.023	1385.196		1249.539	1448.845	2297.147
2009/09	992.681	1085.602	1209.605	1444.574	1206.267	1306.617	1489.508	2379.404

Figure 1

Histogram of Count Data with Poisson Fit



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