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Modeling Contagion among Customers Using Store Scanner Data

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ABSTRACT

While literature has pointed out the imperativeness for marketers to find and understand the presence of social influence in a retail environment, the existent empirical research on social influence commonly recognize consumers' neighbors, friends or acquaintances as their reference groups for purchase and ignore one very important possible reference group: other customers who are right in the retail setting; and by far little research has examined or quantified the impact of people's purchase may have on other customers in the retail environment using real purchase data. Using scanner data from a fashion mall, this research introduces meeting probability as a measure of the likelihood of visual contact among individuals in the store, empirically models the interactions among them, and finds the evidence of in-store contagion that the probability of an individual customer to buy a product changes as a result of observation of other customers' purchase of the same product after controlling for customer's personal preference, common fashion trend and marketing activities. By incorporating and estimating the heterogeneity of both the latent characteristics of attractiveness and susceptibility as well as brand preference across customers via MCMC approach, the model explores the possible positive as well as negative contagion effects at the individual level, and may serve as preliminary reference for retailing practitioners seeking to identify natural individual influential and susceptible customers to be targeted.

Keywords: Contagion, social influence, latent characteristics, choice model, MCMC

INTRODUCTION

Everyone makes decisions not only on the basis of his or her own individual experiences but also on that of the observed or talked experiences of others (Hamblin et al., 1979). Being a member of the society, a consumer could be influenced by the verbal communication or nonverbal observation with other people through certain channels when making purchase decisions (Mahajan, Muller and Bass 1990). Effects of social influence on consumer's purchase decision have been empirically examined by prior studies in various terms like "neighborhood effect" (Case 1991; Bell and Song 2007), "contagion" (Van den Bulte and Lilien 2001; Albuquerque, Bronnenberg and Corbett 2007; Manchanda, Xie and Youn 2008; Iyengar, Valente and Van den Bulte 2008), "interdependent preference" (Kapteyn, et al., 1997; Yang and Allenby 2003; Yang, Narayan and Assael 2006), "peer effects" (Nair, Manchanda and Bhatia 2006) and "social interactions" (Hartmann, et al., 2008) etc, wherein consumers' family members, neighbors, friends, colleagues or other acquaintances were proved to be a major source of social influence on purchase decision.

However, in a variety of decision-making scenarios individual customers may be influenced more by exposure to each other than to other influence sources (Katz and Lazarsfeld 1955). For example, since the clothing market is especially characterized by highly unplanned buying with many decisions made at the point of purchase (Christopher and Peck 1999), the presence of social influence from interaction among individual customers in a retail environment is likely to be far more powerful predictors of consumer's purchase behavior in fashion retailing (Cholachatpinyo et al. 2002). We may imagine the following scenario: in a big fashion mall, there are too many items for anyone to wade through. A customer, called I, is tired after several unsatisfactory tries. In such an environment of choice overload, it is possible that customer I comes across another customer, called J, who is trying on some type of clothes and suddenly that type of clothes becomes appealing (or undesirable) for customer I. This scenario shows how a customer's preference might be influenced based on the choice of another customer in that same store even if they are neither acquainted nor ever talked with each other. The phenomenon can be explained by the social learning theory which suggests that one individual can learn from observation of other people's activity consciously or unconsciously, and this process does not necessarily involve a verbal exchange, nor merely occur among acquaintances (Miller and Dollard 1941; Bandura 1977, 1986; Rogers 1995). But except for theory and anecdotal evidence, little research has empirically examined the impact of people's purchase in the store may have on other customers' choice using individual-level transactional data at the retail store. We name such effect as "in-store contagion", which means the probability or motivation of one individual to buy a product changes as a result of observation of the other's purchase of the same product in the store.

Recently, more and more firms are conducting Word-of-Mouth marketing and some firms rely heavily on those "connectors" who have lots of social ties and less on those natural trendsetters or influencers who define trends and influence others naturally; and some firms even hire actors to pose as the average. The unrestraint exercise of buzz tactics seems to have degraded all the social ties into business transactions and diluted the effectiveness of the approach and make people skeptical and annoyed. (http:// knowledge.wharton.upenn.edu/ article.cfm?articleid= 1105). To examine the contagion effects happened during natural interactions among customers in a retail setting at the individual level will help firms to identify natural influential and susceptible customers thus to design targeting plan as well as longterm customer retain and resource allocation strategies.

LITERATURE

Social Influence from Various Sources in Various Contexts

Since the Bass model (Bass 1969) proves that the number of adopters who purchase a product by a given time is a function of social contagion probability, researchers have been modeling specific forms of social contagion in various contexts and domains. For example, Case (1991) found spatial correlation in household rice consumption such that households gain utility in consuming bundles similar to those consumed by their neighbors. Kapteyn, et al., (1997) found household consumption of a category is a function of the mean expenditures on that category of the referenced social group of the household with similar education, age and job characteristics, and across 6 different categories such correlations' magnitude were found to be in a decreasing order as housing, medical care, education and entertainment, clothing, transportation and food. Yang and Allenby (2003) found the preferences for Japanese-made cars are associated across consumers with geographic proximity or demographic similarity. Yang, Narayan and Assael (2006) found that individual consumption of a TV program is influenced by his or her spouse. Nair, Manchanda and Bhatia (2006) found that physician prescription is influenced by their referenced colleague or specialists. Bell and Song (2007) found the probability of the first online purchase trial in a ZIP region is positively influenced by prior triers in adjacent ZIP regions.

Manchanda, Xie and Youn (2008) found physician’s adoption of a new drug is influenced by closely connected colleagues. Hartmann and Yildiz (2008) found golfer’s consumption depend on his or her pal partner’s decision. In all these contexts, the sources of social influence on purchase decision are consumers’ neighbors, family members, friends, colleagues, demographical peers or other acquaintances, and the effects of social influence are positive. As one exception, Cowan, Cowan and Swann (1997) analytically model the diffusion process of innovation under the assumption that there exist three types of reference group: peer, contrast and aspiration groups, and derives steady state and dynamic properties of the distribution of consumption. However, this model is at the aggregate level and does not identify “who influences whom” individually.

For the retailing domain, there are few empirical modeling works on social influence. Theoretically, Montoya, Mandel and Nowlis (2005) proposed that to reduce cognitive effort, shoppers may simply choose the brand that they perceive most others are buying using the shelf space as an indicator without direct interaction with other consumers. Using field experiments, researchers found customer’s evaluation toward a touched product by another customer is moderated by that customer’s personal attractiveness: the product evaluations are negative when the focal customer perceive a product has been physically touched by another (unattractive) customer, while positive (and higher) when perceiving a product has been physically touched by a (more) attractive customer (Peck and Childers 2003; Argo, Dahl, and Morales 2006; Argo, Dahl and Morales 2008). These research remind us the existence of both positive and negative (due to “the wrong people”) social influence in the retail setting that we need to consider when we try to model the in-store contagion effect.

Data Used

By far different types of data were used to capture the proposed social influence in various contexts. For example, spatial-temporal data has been used to track diffusion processes among early and later adopters but usually at an aggregate level such as zip-code or county rather than at the individual consumer level (Albuquerque, Bronnenberg and Corbett 2007; Bell and Song 2007). Online communication data has been analyzed to construct online community networks (Richardson and Domingos 2002; Brown, Broderick and Lee 2007) and such networks have been used by advertisers to tap into niche communities (Carter 2006). However, data from online communities may ignore offline interactions among consumers and frequently lacks any real purchase behavior information. Besides, in the pharmaceutical industry context, researchers surveyed individual physicians to obtain names of those who influence them (Nair, Manchanda and Bhatia 2006; Iyengar, Valente and Van den Bulte 2008). However, this self-reported social ties information may be difficult to obtain within a retail environment since customers might not be acquainted with those who influence them when they meet in the store, or are even not consciously realizing that they are influenced by others. More recently, field experiment data was used to examine the response of customers to other attractive "customers" in the retail environment (Argo, Dahl and Morales 2008), but the experimental manipulation of "attractive" agents could not help firms to identify natural influencers in their customer pools.

One may suggest that the ideal data for investigating the in-store contagion and identifying natural influencers is the video data automatically collected from the cameras located around the store. It may actually involve economic, technical and ethical problems. First, stores are unlikely to install cameras everywhere and the manual analysis of the video content is time consuming and even impossible considering the length of data recorded during continuous store operation. Second, the computer-aided observation technique that automatically counted customer movements from standard in-store video can hardly track and identify large number of the customers in the store at the same time (Newman, Yu and Oulton 2002). Third, ethical issue of privacy may arise due to in-store surveillance.

Then we think of using store scanner data collected through optical scanning of the product's code when purchased by individual customers, the very natural, objective and easy to get information that have many special advantages (Guadagni and Little 1983), to examine the contagion effect for purchase happened in the store among individual customers.

Model Framework

To provide evidence that social interaction affect product adoption, researchers need to model the relationship between consumers' social communication linkages and consumers' adoption behavior. For example, Nair, Manchanda and Bhatia (2006) modeled individual physician *i*'s prescriptions dependent on his/her reported opinion leader *j*'s prescriptions using a random intercept framework $y_i = \alpha_i + \delta y_j + \ldots$ where the fixed coefficient δ tests the effect of social influence.

When it comes to the situations that no explicit communication linkages between consumers can be observed, as the situations typically tackled by the spatial or epidemiological studies, the geographic proximity or other characteristics of consumers are used as a proxy for social communication. For example, Spatial Autoregressive model (Yang and Allenby 2003) builds the social interaction into a part of covariance structure by specifying the augmented error terms to be correlated across individual consumers with geographic proximity or demographic similarity as $\theta_i = \rho W \theta_j + u_i$, where the matrix W measures the geographic demographic linkages between individuals *i* and *j* , and the single parameter ρ tests the overall association effect (Rossi, Allenby and McCulloch 2005). Further, having access to the information of time sequence of adjacent regions' adoption, Bell and Song (2007) modeled the social influence in a framework like $y_{it} = \alpha_i + \delta W y_{j,(t-1)} + \ldots$, while the unit of the model is region rather than individual.

Rarely offering evidence to support the reference-group specifications (Manski 1993), econometrics models studying social effects usually take the communication linkages between focal subjects and their reference group who are similar in social or demographic attributes for granted, and examine how an individual's behavior is affected by his or her referenced agent in a random coefficients model framework like $y_i = \alpha_i y_j + (\beta_i z_j +)\ldots$ (Hartmann et al. 2008), where individual *i*'s outcome action y_i is directly dependent on the referenced agent *j*'s action y_j , as well as agent *j*'s other, usually observable, characteristics z_j . The effect of social influence is then tested through the individual specific parameters α_i and β_i toward these two parallel influence. These econometric models are capable of disentangling the individual contributors to the social effects and were widely adopted in the marketing field (Yang, Narayan and Assael 2006; Nair, Manchanda and Bhatia 2006; Hartmann and Yildiz 2008).

However, as mentioned before, there exists potential negative social influence due to the unobservable characteristics ζ_j of certain “wrong people” *j*, (i.e., the effect of the referenced action y_j is not linearly separated from the unobservable characteristics of the referenced agent ζ_j but rather multiply moderated by it, as $y_i = \alpha_{0i} + \alpha_{1i}\zeta_j y_j + \ldots)$ this contingent nature of social effect is not reflected by the above model frameworks.

Focal Products

Finally, most past research has examined the social influence effects based on only one or several specific products. This study will examine the effect based on large number of different products sold by a fashion mall.

Therefore, different with the past literature, this research is to find the contagion effect among customers in the retail environment, specifically, it will examine (1) whether there is empirical evidence for in-store contagion among customers using scanner data across large number of fashion products, and (2) what the nature and magnitude of such in-store contagion is at the individual level. We will introduce a proxy measure for the unobservable interaction between individual customers in the store and will capture the contingent reference effect by specifying the heterogeneity of both the attractiveness of the contagion source and the susceptibility of contagion recipient customers, and estimating these parameters using MCMC method.

MEASURES

Observed Choice of a Contagion Source Customer

The observed choice of a potential contagion source customer *j* who purchases earlier may exert influence on their respective contagion receiver customer *i*, and it depends on: a) whether they meet in the retail store, and b) choices of customer *j*. Let's begin with how we specify whether or not two customers *i* and *j* meet within the store.

For a customer *i*, we calculate the exposure to his or her respective customer *j* using the construct of meeting probability i.e., the probability that they might see each other in the store. We use their checkout times from the retail store to ascertain this probability. Similar to the research in epidemiology where spatial adjacency is used as an index of the physical contact between contagion source and receiver, in our context the meeting probability is a measure of visual contact likelihood between two customers. The higher is the meeting probability, the greater is the possibility that the customer *i* observes customer *j*'s behavior in the store and learns from it.

Figure 1 illustrates how to calculate the meeting probability via the use of geometry. Any point within the rectangle may represent the arrival time of customer *i* and customer *j* at a certain place in the store; the line Y equals to X represents they arrive at the same time, above (below) that line means customer *i* (customer *j*) arrives later. Suppose both customers stay at the same location for 5 minutes, then the meeting probability equals to the shaded area, which is between the lines of Y equals X plus and minus 5, divided by the total area of the rectangle.

Insert Figure 1 here

In our context, we know the check out times of each customer; how long they spend between intermediate checkouts[1] and thus can estimate the total time each customer spends for a shopping trip. In addition, we also know the number of items a customer purchases in the trip. This gives the average time a customer spends on purchasing one unit of product. We use this information from each customer to find the meeting probability between any two customers.

Having operationalized both the meeting probability, for a product *l* and purchase occasion *t* for customer *i*, the past, same day, choice of customer *j* observed by customer *i* is captured through the term $Y_{jlt^-} MP_{ijlt}$,where MP_{ijlt} captures the meeting probability of customer *i* and *j* for the purchase occasion on that day, and Y_{jlt^-} (= 1 or 0) is a variable representing the prior choice of customer *j* on the same day. We create the variable $Contagion_{ijlt}$, which equals to $Y_{jlt^-} MP_{ijlt}$.

Latent Personal Attractiveness of Contagion Source Customer

Prior research has found that contact with a desirable source (i.e., an attractive person) or an undesirable source generally results in higher or lower evaluations of the recipient object (Morales and Fitzsimons 2007; Argo, Dahl and Morales 2008). We incorporate one latent

[1] In the fashion mall, which has a store within a store format, customers typically checkout multiple times within a single visit to the shopping mall.

parameter ζ_j (could be either positive or negative) for each individual potential source customer *j* which represents *j*'s personal attractiveness or stylishness that make customer *j*'s observed choice influential to nearby customers in the store. To capture the personal influence exerted by customer *j* on customer *i*, which may be either desirable or undesirable, we multiply the observed prior choice of customer *j* by customer *i*, $Y_{jlt^-} MP_{ijlt}$, with the latent personal attractiveness of customer *j*, ζ_j , representing that the observed prior choice of an attractive (or undesirable) customer *j* will send out a positive (or negative) impact to customer *i*.

Product Popularity

For a particular pair of customers *i* and *j* in purchase occasion *t*, we operationalize the popularity of a product *l* through the daily sales volume of that product from all other customers except for *i* and *j*, divided by 100. This variable helps us control for attractiveness of a product (due to common fashion trend or special promotion or features for the product on that day) as the reason for its purchase by customer *i* and *j* at the same time. For a particular product, this measure can vary across days as on some days a product might have a promotion such as a special display and become temporarily attractive. Thus, using this variable also accounts for the effect of any unobserved feature or display promotions of a product as the reason for its purchase.

Product Promotions

The fashion mall offers promotions such that the greater the discount rate for a product is, the deeper is the promotion. This measure varies across products and can also vary within the same product across days.

Product Attributes

Price

Log of the daily price of the product.

Expensiveness

We control for product expensiveness by including the logged value of the historical average price of that product. It serves as an index of the high or low class of the product.

Product Category

We use variables Proca to indicate whether the product is for men's use only, which equals to 1 if yes and 0 otherwise.

Customer i's brand preference

When making choice, customers' unobservable personal preference toward the brand of a product is not a negligible factor, apart from factors such as price or promotion. Such a personal preference can not be measured properly by mere counting the customer's historical purchase of a brand since the historical choice can be also driven by factors such as product attributes and marketing activities besides the customer's brand preference. To disentangle the impact of personal brand preference and thus control it, we incorporate an individual customer-brand specific latent parameter β_{il} , which is defined as the probability of a customer *i* choosing product *l* due to *i*'s personal brand preference, when otherwise he or she would not have chosen it based on other factors.

MODEL AND ESTIMATION

Model

For any one sequential purchase pair composed of two customers *j* (earlier purchaser and thus the potential contagion source) and *i* (later purchaser and thus the potential contagion receiver), let *l* represent the purchased product and *t* index a shopping occasion when both *i* and *j* or one of them were in the retail store, we model the contagion receiver, *i*'s purchase choice Y_{ijlt} (Y_{ijlt} =1 or 0) conditional on the prior purchase decisions of his/her respective contagion source customer *j*, Y_{jlt^-} .

We specify the utility of customer *i* choosing a product *l* on occasion *t* as the linear combination of covariates such as the product's popularity, price, promotion, expensiveness and category as well as the contagion source customer *j*'s influence, which is a multiplier of *j*'s latent attractiveness ζ_j and the choice of customer *j* observed by customer *i* (the multiplication of customer *j*'s prior choice and the meeting probability of customer *i* and *j*), i.e.,

$$W_{ijlt} = \alpha_{0i} + \alpha_{1i}\zeta_j(Y_{jlt^-}MP_{ijlt}) + \alpha_{2i}Popularity_{ijlt} + \alpha_{3i}Price_{lt}$$
$$+ \alpha_{4i}Promotion_{lt} + \alpha_{5i}Expensiveness_l + \alpha_{6i}Procat_l + \varepsilon_{ijlt} = \eta_{ijlt} + \varepsilon_{ijlt} \qquad (1)$$

Here, we assume that the error term ε_{ilt} has a standard normal distribution, then the probability of the defined utility W_{ijlt} greater than 0 is:

$$\Phi[\eta_{ijlt}] = \int_{-\infty}^{\eta_{ijlt}} \frac{1}{\sqrt{2\pi}} \exp(-\frac{x^2}{2})dx \qquad (2)$$

Suppose that if the utility W_{ilt} pass the threshold 0, customer *i* will choose product *l* on occasion *t*; while under certain probability, due to customer *i*'s other unobservable tastes such as brand preference toward the product *l*, denoted as β_{il}, *i* still will purchase the product even if the utility W_{ilt} defined in equation (1) does not pass the threshold 0. Therefore the probability of customer *i* choosing a product *l* on occasion *t is*:

$$P(Y_{ijlt} = 1) = \Phi(\eta_{ijlt}) + \beta_{il}[1 - \Phi(\eta_{ijlt})] \qquad (3)$$

If the probability $\beta_{il} = 0$, the model reduces to

$$P(Y_{ijlt} = 1) = \Phi(\eta_{ijlt}) \qquad (4)$$

Bayesian Estimation of the Model

Using a Markov Chain Monte Carlo algorithm, we can simultaneously estimate the individual parameters $(\boldsymbol{\alpha}_i, \zeta_j, \beta_{il})$ for both of i-type and j-type customers who may interact and have multiple links between each other. The estimation approach is based on the method proposed by Johnson and Albert (1999), but extends it to incorporate observable covariates and thus additional parameters for those covariates, and to allow for a person-brand specific baseline purchase effect, in a setting of multi-occasion outcomes and possible sparse linkages. (See the Appendix for detail.)

Before discussing the empirical parts, it will be worthwhile to discuss past literature that has focused on the identification of causal contagion effect in the presence of other potential confounding factors (Manski 1993, 2000; Moffitt 2001). This literature indicates several other effects that should be considered before evidence of social contagion can be accepted. These are (1) Endogenous group formation, which means the correlation in behavior is actually due to similar tastes rather than causal effect of one's behavior on another. (2) Correlated unobservables, which arise when influentials and imitators face similar environments, for example, common marketing activities. (3) Simultaneity bias, which arises when the pair of customers mutually influence each other. We address these confounds in several ways. First, we estimate an individual-specific intercept α_{0i} and brand preference parameter β_{il} which controls for individual brand preference and other unobservable taste. Second we include the product's promotion (discount rate) and the popularity of the product, thus controlling for the common fashion trend and marketing activity as well as other unobservables which might be affecting all customers. Finally we note that the time sequence nature of the purchase data helps us to assume away concerns related to simultaneity.

DATA

We use the scanner data from a fashion mall in Beijing. The data is over a two year period and has no left censoring as we have customer-level purchase information from the day of store launch.

As scanner data provides information regarding when and what customers purchase within the store, we may depict this data as a network with the nodes as customers and directional links among them as the purchase sequence. Figure 2 shows such a simplified network in which A, B, C, ..., Z are customers and different colors represent different products, such as a Hugo Boss dress or a Ralph Lauren Polo shirt.

Insert Figure 2 here

For our analysis, we delete customers who have missing data and those who purchased on less than 8 or more than 200 occasions over the two years of data period. For the remaining ones, we randomly pick 197 pairs from all the possible pairs that have ever sequentially purchased a same product on one day[2]. For each such pair of customers, we have a potential contagion source (termed as customer *j*) and a potential contagion receiver (termed as customer *i*) with the latter being those customers who purchase a same product later than the former in one day. The dataset involves 101 unique j-type customers and 111 unique i-type customers, with possible multiple

[2] In our sample, 90% of the time difference between j-type and i-type customers' same-day, same-product purchases is longer than 37 minutes. This means that those pairs are not likely to be shopping pals who frequently shop together, but rather unacquainted customers shopping in the same store.

linkages among j-type customers and i-type customers. For constructing the final data set for our model, we include observations for each pair of customers when any one of them or both of them were in the store and track all products that have ever been purchased during their total purchase history for each paired customers as alternative choices for them in each purchase occasion. From this data, we use the first 90% observations as the calibrate data for our model and use the last 10% observations as the hold-out dataset to assess the model fit as well as in-sample and out-of-sample prediction accuracy.

Table 1 provides summary statistics and correlation matrix for these covariates for our dataset.

Insert Table 1 here

EMPIRICAL RESULTS

We estimate our models using Markov Chain Monte Carlo methods. We obtain parameter draws based on 5,000 iterations after a burn-in period of 15,000 iterations of the Markov chains, using the R statistics suggested by Gelman and Rubin (1992) as convergence criterion. To avoid autocorrelations between successive draws we keep a total of 1000 recorded draws after the burn-in period for each parameter at every 5^{th} draw.

We estimate two full models specified as (3) and (4) and six null models with slight variations to these two full models. Null Model 1-1 and 2-1 are similar to the corresponding full models except that it contains no latent attractiveness trait parameter ζ_j. Null Model 1-2 and 2-2 is similar to the full models except that the contagion term is defined merely as Y_{jlt^-} without multiplied by Meeting Probability MP_{ijlt}. Null Model 1-3 and 2-3 are similar to the full models except that it contains neither latent attractiveness trait parameter ζ_j nor Meeting Probability MP_{ijlt}. We also estimate a standard random intercept model (includes an individual specific random term normally distributed with mean 0 and standard deviance sigma that controls for individual i-type customer's unobservable preference) and a standard probit model as well as their variation forms with Meeting Probability MP_{ijlt}.

Table 2 and 3 show the estimates for the random intercept model and probit model where the contagion terms are defined as Y_{jlt^-} multiplied by Meeting Probability MP_{ijlt}. Here we note that the mean contagion effect is significantly positive. The estimates also indicate that for a certain product, higher price decreases purchase and the promotion exert significant positive effect on customers' purchase. In addition, all else being equal, high end products (i.e., with higher level of expensiveness) have greater purchase probability, and men-use products have greater purchase probability than other products.

Insert Table 2 and 3 here

Table 4 and 5 show the posterior estimates for the full models 1 and 2 and the six Null Models for *i*'s parameters (α_i) of the 20 i-type customers as ordered in our dataset with the smallest and largest susceptibility estimate.

Insert Table 4 and 5 here

Table 6 shows *j*'s parameters (ζ_j) of the 20 j-type customers as ordered in our dataset with the smallest and largest attractiveness estimates in the full models. We note that the coefficient estimates are largely consistent across the models.

Insert Table 6 here

For model comparison, we calculate the log-marginal likelihoods (LML), the out-sample prediction performance for each model, and the Bayesian deviance information criterion (DIC). Table 7 shows these criteria for the Full Models and the Null Models. A comparison of these criteria for the 12 models shows that Full Model 2 fits the in-sample data best and Full Model 1 has the best performance on hold-out-sample fit and best Bayesian deviance information criterion which penalizes for the complexity of the Bayesian model (Spiegelhalter, et al. 2002). The results also reveal that including both latent attractiveness and meeting probability is important for in-sample and out-sample fit, and including the personal brand preference will improve out-smaple fit.

Insert Table 7 here

Finally, using the individual-level parameters, we calculate the difference in the potential contagion recipient customer's purchase probability when the corresponding potential contagion source member buys or does not buy. We find that, across all purchase occasions involving the identified one attractive j-type customer (with a significant positive latent attractiveness estimate) in the dataset, there will be an average increase of 297.16% in the probability of purchase from the i-type customer if the attractive j-type customer buys, versus if the j-type customer does not buy. This will result to a total increase of about 41,841 RMB purchase value from the i-type customers. The total increase also suggests that in our sample, the identified one most attractive j-type customers, by exerting influence on her corresponding i-type customers, are worth 41,841 RMB more than what she herself has purchased (22,588RMB). These numbers indicate a social spillovers of the attractive which is around 185.24% of her intrinsic value. We also find that, across all purchase occasions involving the attractive j-type customers (with a positive latent attractiveness estimate) in the dataset, there will be an average increase of 55.26% in the probability of purchase from the i-type customer if the corresponding attractive j-type customer buys, versus if the j-type customer does not buy. This will result to a total increase of about 89,325 RMB purchase value from the i-type customers. The total increase also suggests that in our sample, the 54 attractive j-type customers, by exerting influence on their corresponding i-type customers, are worth 89,325 RMB more than what they themselves have purchased (355,658RMB). These numbers indicate a social spillovers of those attractive which is around 25.12% of their intrinsic value.

CONCLUSIONS AND IMPLICATIONS

From the sample of about 200 customers randomly picked from the fashion mall's customer pool (more than 20,000), we find the effect of in-store contagion after controlling for personal brand preference, common fashion trend and marketing promotion, and we identify 1 natural influential customer and 5 customers significantly susceptible to other customers' influence. The economic spillover due to the influential customer's influence is noteworthy for retailing practitioners.

Theoretical Contribution

While some researchers pointed out that it is imperative for marketers to find and understand the presence of social influence in a retail environment, the existent empirical research on social influence commonly ignored one very important possible reference group: nearby unacquainted customers right in the retail environment. This research is trying to fill out this gap by examining (1) whether there is empirical evidence from real purchase data for the existence of in-store contagion among customers; and (2) what the magnitude of such in-store contagion is at the individual level.

Second, since neither the residence distance nor consumer self-reported social network could help capture preference interdependency between unacquainted customers in the store; and since the economic, technical and ethical problem may preclude researchers from using store video which might accurately record any behavior of customers (if there even exist such video tapes for large number of different customers and different products within a retail setting), this research introduces an approach to measure the likelihood of meeting among individual customers, which can be applied to a lot of contexts wherein micro-level social interactions among people need to be investigated.

Third, by incorporating and estimating both the individual susceptibility of potential contagion receiver customers and the personal attractiveness parameter of potential contagion source customers simultaneously, our model allows for the exploration of the potential negative contagion effect contingent on the latent characteristics of source customers.

Finally, most past research has examined the contagion effect based on only one or two specific products. The use of scanner data from a fashion mall allows this research to find evidence for contagion effects based on large number of different products.

Managerial Implication

Marketers are finding that one of the most effective techniques is to market specifically to those influential customers… For instance, the CEO of Crocs, Ron Snyder, noted: "you want the right people on the bus early" (Anderson, 2006). The estimates of the latent attractiveness and susceptibility for individual customers based on our model may serve as preliminary reference for retailing practitioners seeking to identify natural individual influential and susceptible customers to be targeted while avoiding the high cost and ethical dilemma incurred by using other data such as in-store video tape. Using the coefficients estimates from the model, firms can measure relative effectiveness of different marketing vehicles (including the social influence in the retail environment) and thus design individual specific promotion plan. In addition, firms may pay special attention on those identified attractive influential customers, retain them carefully, examine their preference and needs, since "everyone else pays attention to the gadgets they use, as well as the clothes they wear, the food they eat or where they dine, and the cars they drive…" (Daniel B. Honigman 2007) and their choice will be the fashion.

Limitations and Future Research

The sample size is about 200 people in our study. In the future, we may use larger sample to abtain a more wholistic view of the interactions among in-store customers.

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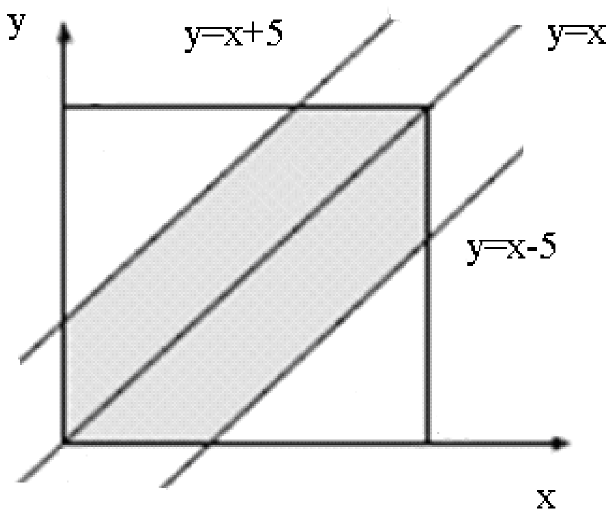

Figure 1: Geometric representation for calculating the meeting probability between two customers. In the figure, the x-axis denotes the arrival times for Customer *j* and the y-axis denotes the arrival times for Customer *i*. The shaded area represents the intersection of the two customers within a 5 minute interval.

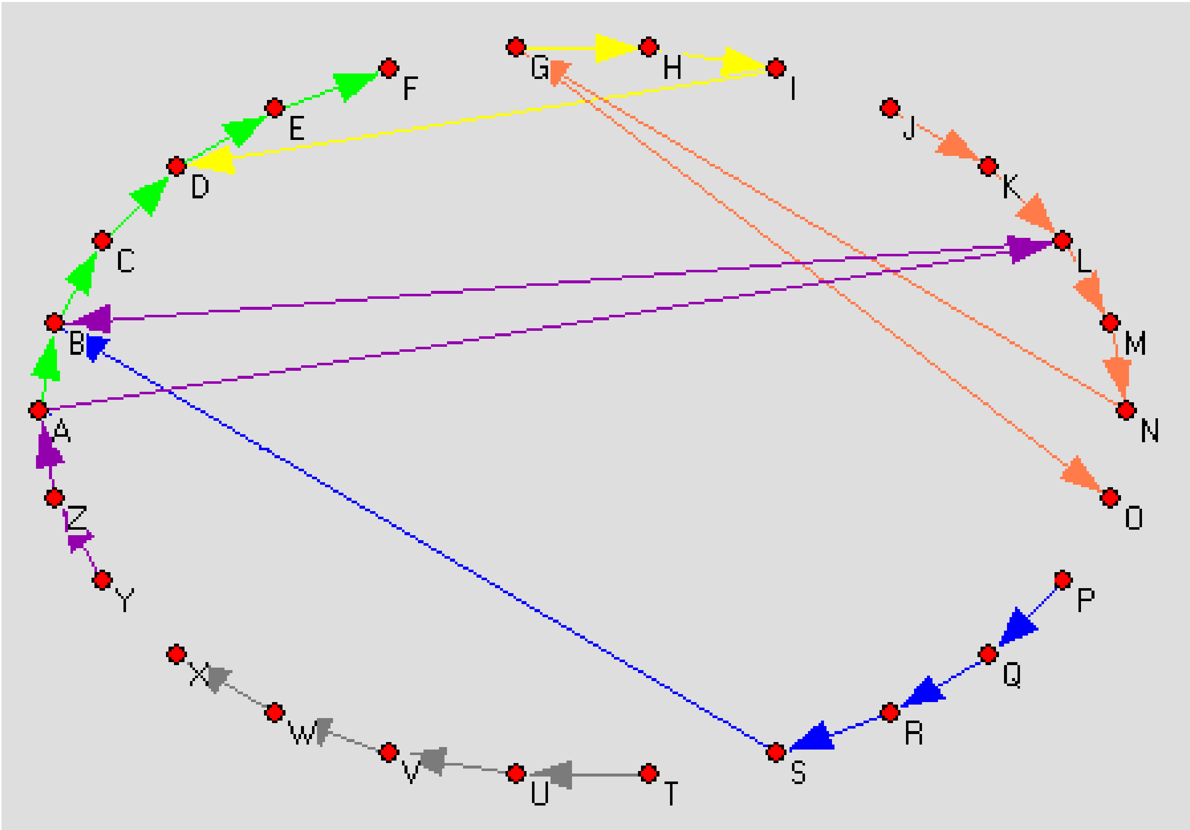

Figure 2: Customer Network Based on Purchase Sequence: The directional links depict the purchase sequence among customers. The different colors denote different products.

Table 1: Descriptive Statistics and Correlations among Covariates

Variable	*Mean*	*Std*	*Min*	*Max*						
Contagion	0.0006	0.0188	0	1	1					
Popularity	0.0222	0.0702	0	3.6900	0.0767	1				
Price	5.1788	0.8154	0.7459	9.3770	-0.0101	-0.1068	1			
Promotion	0.0783	0.1690	0.0000	0.5349	0.0438	0.3369	0.0737	1		
Expensiveness	5.2240	0.7685	2.8608	7.1487	-0.0082	-0.0882	0.9310	0.1183	1	
Proca	0.1125	0.3159	0	1	-0.0081	-0.0170	-0.0795	-0.0427	-0.0850	1
MP	0.0045	0.0475	0	1	0.3938	0.0482	*0.0020*	0.0184	*0.0036*	*-0.0046*

Notes: Values computed on a single observation for each occasion, N=95,737.

All correlations except for those in italics are significant at $p<0.05$.

Table 2: Estimates for the probit model with MP

Coefficient	*Estim*	*SE*	*2.5%*	*97.5%*	*Pr > ChiSq*
Intercept	-1.8392	0.0561	-1.9491	-1.7293	<0.0001
Contagion	1.9569	0.2275	1.5110	2.4028	<0.0001
Popularity	1.4888	0.0720	1.3477	1.6299	<0.0001
Price	-0.2667	0.0227	-0.3111	-0.2222	<0.0001
Promotion	1.1321	0.0420	1.0498	1.2143	<0.0001
Expensiveness	0.2177	0.0249	0.1689	0.2664	<0.0001
Proca	0.0841	0.0257	0.0336	0.1345	0.0011

Table 3: Estimates for the random intercept model with MP

Coefficient	*Estim*	*SE*	*2.5%*	*97.5%*	*Pr>|t|*
Intercept	-1.4620	0.0636	-1.5881	-1.3360	<0.0001
Contagion	1.9827	0.2306	1.5258	2.4396	<0.0001
Popularity	1.4103	0.0735	1.2648	1.5559	<0.0001
Price	-0.2901	0.0230	-0.3356	-0.2446	<0.0001
Promotion	1.1105	0.0437	1.0239	1.1970	<0.0001
Expensiveness	0.2174	0.0252	0.1676	0.2673	<0.0001
Proca	0.0846	0.0269	0.0313	0.1379	0.0022
Sigma^2	0.0479	0.0090	0.0302	0.0657	<0.0001

Table 4: Posterior Estimates for Part of i's Parameters ($\boldsymbol{\alpha}_i$) for Full Model 1 and Null Model 1-1 to 1-3

Full Model 1				Null Model 1-1				Null Model 1-2				Null Model 1-3			
α_{1i}	α_{2i}	α_{3i}	α_{4i}	α_{1i}	α_{2i}	α_{3i}	α_{4i}	α'_{1i}	α_{2i}	α_{3i}	α_{4i}	α'_{1i}	α_{2i}	α_{3i}	α_{4i}
35.015	0.156	-0.287	-0.733	29.871	0.223	0.298	-4.168	24.409	0.149	-0.454	1.628	18.192	0.303	-0.794	-5.248
6.669	**1.604**	**-0.491**	**0.606**	**1.376**	**1.599**	**-0.491**	**0.629**	0.165	**1.625**	**-0.495**	**0.609**	0.165	**1.585**	**-0.485**	0.591
32.851	**3.400**	-0.193	0.636	**36.781**	**3.463**	-0.183	0.618	23.332	**3.575**	-0.179	0.595	0.961	**3.551**	-0.153	0.681
34.352	**3.798**	-0.103	0.582	**5.443**	**3.806**	-0.102	0.574	24.110	**3.728**	-0.099	0.540	0.412	**3.759**	-0.102	0.515
10.846	0.266	**2.090**	7.908	1.729	0.467	**1.959**	**4.001**	24.172	0.429	**2.102**	6.978	0.509	0.374	**1.959**	4.085
18.061	**-3.546**	**0.605**	**4.423**	**5.262**	**-3.184**	**0.598**	**4.373**	0.424	-3.280	**0.567**	**4.698**	**0.486**	**-3.418**	**0.526**	4.542
15.012	**3.581**	-0.245	0.542	2.553	**3.541**	-0.169	0.214	25.290	**3.594**	-0.192	0.516	0.934	**3.528**	-0.127	0.263
1.066	**1.333**	-0.031	**4.755**	**1.287**	**0.924**	-0.009	**8.502**	0.162	**1.340**	-0.049	**5.789**	0.235	**1.237**	-0.050	5.461
32.347	-0.216	0.686	-2.127	**41.894**	-0.178	-0.347	-1.011	28.315	-1.089	-0.903	11.703	**17.768**	-0.712	-0.387	13.113
5.041	**0.732**	**-0.183**	**1.146**	**2.335**	**0.738**	**-0.183**	**1.142**	0.143	**0.729**	**-0.174**	**1.156**	**0.222**	**0.700**	**-0.177**	1.141
41.162	1.058	-0.011	**3.146**	**42.531**	0.999	0.007	**2.757**	28.219	0.758	-0.052	**2.806**	**1.246**	0.695	-0.040	2.870
40.772	-0.126	-0.613	5.623	**35.070**	-0.363	0.152	3.702	26.151	0.156	-0.959	5.759	14.273	0.376	-1.659	0.230
35.381	3.740	1.070	4.515	21.412	3.219	0.883	4.713	25.833	3.100	1.075	6.253	2.834	2.807	1.024	4.636
17.123	**5.826**	-0.269	**11.382**	6.061	**5.743**	-0.277	**13.517**	23.986	**5.837**	-0.323	**10.164**	0.644	**6.017**	-0.296	14.738

10.664	0.189	**-0.705**	**0.822**	0.828	0.175	**-0.707**	**0.816**	0.198	0.183	**-0.708**	**0.818**	0.169	0.151	**-0.709**	0.791
15.670	2.564	0.365	-0.239	5.806	3.224	0.819	-0.350	21.108	2.292	0.538	0.674	2.035	3.511	0.201	-0.403
37.569	1.725	-1.122	0.444	**41.427**	1.752	-1.098	0.459	23.017	1.702	**-1.188**	0.463	0.860	1.784	**-1.215**	0.376
16.931	**7.089**	-1.255	**6.603**	35.604	**6.775**	**-1.320**	**5.060**	22.061	**7.724**	-1.097	**4.142**	0.924	**7.643**	-1.133	4.549
37.845	0.235	-0.900	0.462	25.558	-0.048	-1.115	1.061	24.466	0.151	-1.197	1.122	2.522	1.234	-0.043	-1.684
32.839	**8.233**	-0.443	**1.423**	30.146	**8.392**	-0.443	**1.367**	22.160	**8.252**	-0.415	**1.379**	0.898	**8.177**	-0.438	1.383

Notes: The numbers in bold indicate that the 0 lies outside of the 95% interval of the estimates.

For parsimony, we include in the table only the parameter estimates of variables Contagion, Popularity, Price and Promotion of the 20 i-type customers as ordered in our dataset with smallest and largest susceptibility estimate for the full model.

Table 5: Posterior Estimates for Part of *i*'s Parameters ($\boldsymbol{\alpha}_i$) for Full Model 2 and Null Model 2-1 to 2-3

Full Model 2				Null Model 2-1				Null Model 2-2				Null Model 2-3			
α_{1i}	α_{2i}	α_{3i}	α_{4i}	α_{1i}	α_{2i}	α_{3i}	α_{4i}	α'_{1i}	α_{2i}	α_{3i}	α_{4i}	α'_{1i}	α_{2i}	α_{3i}	α_{4i}
7.876	**1.595**	**-0.490**	**0.615**	**1.355**	**1.600**	**-0.489**	**0.601**	0.145	**1.641**	**-0.489**	**0.604**	0.161	**0.111**	**-0.395**	**0.100**
35.917	**3.371**	-0.161	0.687	**37.409**	**3.429**	-0.157	0.612	27.625	**3.529**	-0.133	0.619	0.949	**0.260**	-0.117	0.107
32.053	**3.797**	-0.094	0.574	**5.257**	**3.840**	-0.108	0.516	23.593	**3.810**	-0.118	0.509	0.407	**0.276**	-0.083	0.080
13.526	-0.195	0.803	1.672	21.876	2.058	1.642	-3.080	25.022	0.267	0.815	0.837	8.146	0.669	3.538	-2.389
8.067	0.377	**1.571**	**3.225**	1.603	0.323	**1.633**	**3.249**	23.843	0.395	**1.568**	**3.160**	0.447	0.034	**1.338**	**0.524**
28.116	-0.617	-0.595	1.934	4.384	-0.564	-0.574	1.851	24.263	-0.590	-0.574	1.942	0.615	-0.057	-0.430	0.305
17.715	1.836	**0.943**	1.108	1.969	1.681	**1.013**	1.000	25.823	1.744	**0.966**	1.064	1.258	0.109	**0.866**	0.166
17.150	**3.564**	-0.244	0.380	2.249	**3.397**	-0.241	0.105	23.858	**3.454**	-0.248	0.302	0.868	**0.288**	-0.194	-0.017
29.147	2.454	0.282	1.310	8.702	2.831	0.417	2.101	25.316	2.617	0.208	1.891	0.654	**2.990**	3.473	-1.565
1.020	**1.248**	-0.035	**6.390**	**1.395**	**1.061**	-0.043	**6.148**	0.172	**1.285**	-0.028	**6.356**	0.231	**0.090**	-0.024	**0.897**
4.721	**0.736**	**-0.179**	**1.150**	**2.337**	**0.735**	**-0.181**	**1.147**	0.138	**0.738**	**-0.164**	**1.165**	**0.227**	**0.049**	**-0.143**	**0.194**
41.348	1.074	0.023	**2.574**	**44.186**	1.028	0.003	**2.584**	29.690	0.957	-0.048	**2.531**	1.095	0.067	-0.014	**0.441**
28.036	-0.406	-0.363	2.969	27.002	-0.309	-0.248	2.812	23.864	-0.233	-0.819	3.379	0.746	-0.062	-0.669	0.576
16.165	4.324	0.239	**4.237**	25.765	4.239	0.243	**4.228**	24.110	**4.944**	0.276	**3.920**	0.710	**0.843**	0.051	0.692

16.945	**5.547**	-0.501	**2.879**	5.925	**5.610**	-0.523	**2.884**	23.951	**5.509**	-0.520	**2.964**	0.488	**0.463**	-0.424	**0.484**
13.425	3.324	0.747	-1.299	**2.809**	3.291	0.842	-1.550	10.546	3.395	0.607	-1.348	1.031	**0.458**	0.489	-5.698
39.734	**1.785**	-0.793	0.284	**42.424**	**1.795**	-0.809	0.316	23.509	1.726	-0.849	0.409	0.854	**0.139**	-0.743	0.038
37.133	**6.721**	**-1.337**	**4.164**	29.761	**6.793**	**-1.309**	**4.190**	22.739	**7.637**	**-1.155**	**3.799**	0.562	**1.146**	-1.009	**0.652**
30.820	**8.295**	-0.446	**1.332**	28.613	**8.278**	-0.445	**1.331**	24.321	**8.313**	-0.443	**1.338**	0.822	**0.761**	-0.355	**0.208**
42.191	**5.404**	-0.109	**4.080**	29.638	**5.317**	-0.128	**4.127**	26.506	**5.891**	-0.067	**3.954**	0.909	**0.668**	-0.062	**0.662**

Notes: The numbers in bold indicate that the 0 lies outside of the 95% interval of the estimates.

For parsimony, we include in the table only the parameter estimates of variables Contagion, Popularity, Price and Promotion of the 20 i-type customers as ordered in our dataset with smallest and largest susceptibility estimate for the full model.

Table 6: Posterior Estimates for Parameter (ζ_j) for the full and null models

Full Model 1	Null Model 1-2	Full Model 2	Null Model 2-2
0.599	-0.415	0.624	-0.129
-0.245	0.029	-0.440	0.036
0.959	0.200	0.989	0.202
1.013	-0.013	0.964	-0.035
0.566	0.033	0.567	0.055
-0.457	-0.069	-0.566	-0.026
-0.211	0.259	-0.424	0.146
-0.368	0.166	0.833	0.018
1.409	0.016	**1.230**	0.019
1.171	0.016	-0.268	0.039
-0.285	0.131	-0.309	0.081
-0.774	-0.158	-0.561	-0.169
1.013	0.091	0.797	0.024
0.990	-0.146	1.078	-0.037
-0.428	-0.344	-0.334	-0.355
-0.576	0.034	-0.622	0.026
0.896	0.405	0.931	0.349
-0.362	-0.009	-0.317	-0.025
-0.268	-0.290	-0.302	-0.282
1.867	**0.030**	**1.210**	0.023

Notes: The numbers in bold indicate that the 0 lies outside of the 95% interval of the estimates.

The table includes the smallest and largest estimate of latent attractiveness of the 20 j-type customers as ordered in our dataset.

Table 7: Model Fit Comparison

Model	*Specification*	*LML*	*Hold-out sample Fit*	*DIC*
Full Model 1	$\eta_{ijlt} = \alpha_i^0 + \alpha_i^1 \zeta_j Y_{jlt^-} MP_{ijlt} + \ldots$ $P(Y_{ijlt} = 1) = \Phi(\eta_{ijlt}) + \beta_{il}[1 - \Phi(\eta_{ijlt})]$	-11609	**0.0373**	**23497**
Null Model 1-1	$\eta_{ijlt} = \alpha_i^0 + \alpha_i^1 Y_{jlt^-} MP_{ijlt} + \ldots$ $P(Y_{ijlt} = 1) = \Phi(\eta_{ijlt}) + \beta_{il}[1 - \Phi(\eta_{ijlt})]$	-11652	0.0374	23592
Null Model 1-2	$\eta_{ijlt} = \alpha_i^0 + \alpha_i^1 \zeta_j Y_{jlt^-} + \ldots$ $P(Y_{ijlt} = 1) = \Phi(\eta_{ijlt}) + \beta_{il}[1 - \Phi(\eta_{ijlt})]$	-11691	0.0378	23607
Null Model 1-3	$\eta_{ijlt} = \alpha_i^0 + \alpha_i^1 Y_{jlt^-} + \ldots$ $P(Y_{ijlt} = 1) = \Phi(\eta_{ijlt}) + \beta_{il}[1 - \Phi(\eta_{ijlt})]$	-11702	0.0375	23659
Full Model 2	$\eta_{ijlt} = \alpha_i^0 + \alpha_i^1 \zeta_j Y_{jlt^-} MP_{ijlt} + \ldots$ $P(Y_{ijlt} = 1) = \Phi(\eta_{ijlt})$	**-11578**	0.0394	23627
Null Model 2-1	$\eta_{ijlt} = \alpha_i^0 + \alpha_i^1 Y_{jlt^-} MP_{ijlt} + \ldots$ $P(Y_{ijlt} = 1) = \Phi(\eta_{ijlt})$	-11605	0.0396	23650
Null Model 2-2	$\eta_{ijlt} = \alpha_i^0 + \alpha_i^1 \zeta_j Y_{jlt^-} + \ldots$ $P(Y_{ijlt} = 1) = \Phi(\eta_{ijlt})$	-11631	0.0408	23729
Null Model 2-3	$\eta_{ijlt} = \alpha_i^0 + \alpha_i^1 Y_{jlt^-} + \ldots$ $P(Y_{ijlt} = 1) = \Phi(\eta_{ijlt})$	-11653	0.0402	23814

Random Intercept Model with MP	$\eta_{ijlt} = \alpha^0 + u_i + \alpha^1 Y_{jlt^-} MP_{ijlt} + \ldots$ $P(Y_{ijlt} = 1) = \Phi(\eta_{ijlt})$	-12020	0.0407
Random Intercept Model without MP	$\eta_{ijlt} = \alpha^0 + u_i + \alpha^1 Y_{jlt^-} + \ldots$ $P(Y_{ijlt} = 1) = \Phi(\eta_{ijlt})$	-12047	0.0408
Probit Model with MP	$\eta_{ijlt} = \alpha^0 + \alpha^1 Y_{jlt^-} MP_{ijlt} + \ldots$ $P(Y_{ijlt} = 1) = \Phi(\eta_{ijlt})$	-12299	0.0413
Probit Model without MP	$\eta_{ijlt} = \alpha^0 + \alpha^1 Y_{jlt^-} + \ldots$ $P(Y_{ijlt} = 1) = \Phi(\eta_{ijlt})$	-12330	0.0415

Note: LML is the log marginal likelihood calculated using importance sampling method (Newton and Raftery 1994).

Hold-out sample fit is measured by mean absolute deviation of estimated choice probability and actual choice.

DIC is the Bayesian deviance information criterion based on the posterior distribution of the deviance (Spiegelhalter, et al. 2002).