An Empirical Examination of Voluntary Profiling: Privacy and Quid Pro Quo

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Abstract

Evidence suggests that firms which use customer data analytics perform better than those that do not. However, the current policy of voluntary profiling allows firms to collect and use customer information only if customers voluntarily disclose information with them. Further, surveys and literature show that many customers are not comfortable with firms collecting their information due to privacy concerns. A vast literature has examined customer information disclosing behavior using the privacy calculus. The primary premise of the privacy calculus is that despite strong privacy concerns, customers disclose information if the benefits they can get from disclosure justify the costs of losing privacy, or privacy costs. Based on the privacy calculus, firms and marketers believe that customers voluntarily disclose information in exchange for monetary benefits such as discount coupons or cash rewards. Using transaction data that we collected from a firm that sells skin care cosmetic products on its website, we investigate if there is statistical evidence that shows customers disclose information in exchange for monetary benefits. In line with the privacy calculus, we find that customers with low privacy costs and that expect high benefits from personalized services such as product recommendations are more likely to disclose information. Monetary incentives only work as an effective means to elicit information from customers in the age range of 12 – 21 years old. Customers, on average, and especially customers in the age range of 22 – 54 years old are not likely to disclose information simply as a tradeoff for monetary benefits. Personalized services outweigh monetary benefits in enticing these customers to disclose information.

Keywords: Information disclosing, coupon redemption, privacy calculus, Rx. cosmetics, voluntary profiling, customer data analytics.

1. Introduction

The importance of customer data (a.k.a. big data) and data analytics has been emphasized by academia and industry. Surveys conducted by *MIT Sloan Management Review* and *IBM Institute for Business Value* [40] and *McKinsey & Company* [19] show that firms that use customer data analytics perform better than those that do not. However, the current *voluntary profiling* policy allows firms to collect and use customer information only if customers voluntarily share information with them [17, 18]. Further, surveys [48, 61, 67] and academic literature [41, 53] show that many customers are not comfortable with firms collecting their information. According to Morey et al.'s [48] survey "72 percent of Americans are reluctant to share information with firms because they want to maintain their privacy." Even in today's big data world, firms have limited information about their customers and data analytics is often not as useful as firms thought it would be [20, 21].

The literature has examined the relationship between customers' information disclosing behavior and their privacy concerns (for a review of the literature, see [1, 52, 56]). A large portion of this literature focuses on the tradeoff between the costs (due to privacy concerns) and benefits of disclosing information, known as the *privacy calculus* [4, 13, 50]. The primary premise of this privacy calculus is that despite strong privacy concerns, customers would disclose information if the benefits they can get by disclosing information justify the costs of losing privacy, or privacy costs. The privacy calculus perspective has been confirmed and applied in various contexts, including healthcare [2, 3, 36, 42], online commerce [15, 55, 72], social networking or social interaction services [10, 28, 37, 38, 45, 60], location based services [33, 58, 69, 70], and mobile applications or mobile services [29, 31, 49, 51, 64].

Based on the tradeoff in the privacy calculus, firms and marketers have embraced the belief that customers are willing to disclose information in exchange for monetary benefits such as discounts [21, 25, 54] or even cash [63]. Using surveys and experiments, Hann et al. [23] and Hui et al. [27] show that monetary incentives entice people to disclose information. However, Turow et al. [62] show that customers seem to be engaging in tradeoffs because of *resignation*, rather than *quid pro quo*: customers disclose information because they believe their loss of privacy cannot be stopped regardless of disclosure, not because they seek monetary benefits.

Using the transaction data of 3,382 customers we collected from a firm that sells skin care cosmetic products online, we investigate if customers are willing to disclose information in exchange for monetary benefits. We do this by first investigating the tradeoff between customers' privacy costs and their expected reductions in search costs using proxy measures. We then investigate customers' coupon redemption behavior in relation to their information disclosing behavior. The firm provides personalized services such as product recommendations to reduce customers' search costs using information that customers disclose, thus reductions in search costs are benefits directly related to the information that customers disclose yet are non-monetary. Discount coupons, on the other hand, are strictly monetary benefits but less directly related to the information that customers disclose.

Our study complements and contributes to the literature on privacy calculus in two ways. First, the results from our study are based on customers' actual behavior – their revealed preference based on utility maximization. In contrast, most prior studies about privacy calculus rely on survey data, and, therefore, their results are based on customers' intentions (e.g., [2, 4, 13, 15, 50, 62]). Using experiments, Berendt et al. [7] and Keith et al. [30] show that customers' information disclosing intentions can differ from their actual behavior.[1] Further, Hui et al. [27] and Smith et al. [56] point out some weaknesses of privacy studies that rely on survey data and highlight the need of privacy studies that use actual transaction data. Second, and more importantly, our study investigates

[1] Berendt et al. [7] show that in the context of online commerce, one's information disclosing behavior is not always in line with one's stated privacy preferences and Keith et al. [30] show that in the context of privacy-settings in mobile applications there is only a weak relationship between application user's information disclosing intention and their actual information disclosure.

the relationship between customers' information disclosing behavior and their coupon redemption behavior.

The results from our study show that, in line with our theoretical expectations based on the privacy calculus, although customers that opt-out from the firm's email list and text message list for solicitations (those that likely have high privacy costs) are less likely to disclose information, customers that are first-time website users (those that likely expect high benefits from search supports that the firm provides) are more likely to disclose information. Further, although there is a positive relationship between customers' information disclosing behavior and their coupon redemption behavior in the age group of 12 – 21 years old, in the age group of 22 – 54 years old, and on average, there is an inverse relationship: compared to those customers that do not disclose information, customers that disclose information are less likely to seek and use a discount coupon.

These results provide an important implication for academics and practitioners. It suggests that the firms and marketers may be able to elicit information from customers with strong privacy concerns by providing persuasive non-monetary benefits. The monetary benefits such as discount coupons, on the other hand, may not always work as an effective means to elicit information from customers. Persuasive non-monetary benefits such as personalized services based on disclosed customer data outweigh monetary incentives in enticing customers to disclose information.

2. Hypotheses

The privacy calculus indicates that when customers decide whether to disclose information they engage in a cost-benefit analysis; that is, customers that have high privacy costs are less likely to disclose information, whereas those that expect high benefits from disclosing information are more likely to do so [15]. Using this privacy calculus perspective, we build the following two hypotheses, H1 and H2.

Although there is no general agreement on what privacy is and when a privacy concern arises [14, 53], the literature in information systems and marketing defines privacy costs as costs imposed by unsolicited contacts from firms [24, 44, 52, 57]. Customers with high privacy costs are likely to take actions such as opting-out to avoid these unsolicited contacts; that is, compared to those customers that do not opt-out from the firm's email list and text message list for solicitations, customers that opt-out likely have higher privacy costs. As measuring privacy is nearly impossible, almost all empirical privacy studies rely on some sort of proxy measures [56]. Following these earlier studies, using whether customers opt-out from the firm's email list and text message list for solicitations as proxy measures for their privacy costs, we posit

H1: *Customers that opt-out from the firm's email list and text message list for solicitations are less likely to disclose information.*

One of the major benefits of disclosing information identified by the literature is personalization such as product recommendations [56]. Personalization reduces customers' search costs by providing search supports based on the information that customers disclose [39]; hence, customers that expect higher benefits from such search supports (i.e., more reductions in search costs) are more likely to disclose information [9, 66]. Meanwhile, when customers look for information, they search for their internal knowledge first and then move to external knowledge [16]; hence, first-time users are likely to expect higher benefits from search supports that the firm provides as compared to non-first-time users of a product that likely have sufficient internal knowledge about the product, and thereby, do not likely rely much on external knowledge. Accordingly, we have

H2: Customers that are *first-time users of a product are more likely to disclose information.*

Another key benefit of disclosing information discussed in the literature is monetary rewards such as discount coupons [56]. Hann et al. [23] and Hui et al. [27] show that monetary incentives entice customers to disclose information, i.e., customers that disclose information are more likely to be coupon-prone. The coupon proneness is a customer's propensity to respond to a discount coupon [43]. In addition, it is also a customer's tendency to seek and use a discount coupon [5, 8]. Confirming this, coupon-prone customers are more likely to respond to a discount coupon [26, 34] and are more likely to actually seek and use a discount coupon [11]. Thus, we have: customers that disclose information are more likely to seek and use a discount coupon.

However, Turow at al. [62] show that customers disclose information not because they seek monetary benefits but because they believe that their loss of privacy cannot be stopped by not disclosing. This suggests that customers that disclose information may not be coupon-prone. Further, the findings of Xu et al. [70] are mixed – the relationship between customers' information disclosing intentions and their coupon proneness is either significant and positive or insignificant depending on the personalization approach that the firm uses. Taking these equivocal findings together, we make the following hypothesis:

H3: *Customers that disclose information are more likely to seek and use a discount coupon.*

One stream of literature on coupon redemption focuses on customers' behavioral characteristics such as brand (store) loyalty associated with coupon proneness [5, 47, 65]. These studies show that there is a significant and negative relationship between customers' brand (store) loyalty and their coupon use, i.e., loyal customers are less likely to be coupon prone. Brand (store) loyalty in these studies is defined as repeat purchasing behavior. Similarly, academics and practitioners suggest that customers' loyalty to an online commerce website can be measured using metrics such as visit frequency and repeat purchase rate [32, 71]. Accordingly, we hypothesize

H4: *Customers that visit a website more frequently and that purchase more products from the website are less likely to seek and use a discount coupon*.

Our four hypotheses are summarized in Figure 2.

<< Figure 2 >>

3. Empirical Context and Data

3.1. Empirical Context

We use a firm (hereafter, the firm) that sells skin care cosmetic products known as *Rx. cosmetics* on its online commerce website (hereafter, the website) as the context to test our hypotheses. Rx. cosmetics are products used to treat skin problems such as acne and blackheads; however, a doctor's prescription is not required to purchase these products. The firm only sells Rx. cosmetics and its own brand products on its website.

Before making a purchase, a customer can register with the website by filling out an online registration form. The firm allows a customer to purchase products whether or not they register. A non-registered customer also needs to complete some parts of the registration form (for payment and shipping) to place an order, yet the firm does not store any of this information in its database. Further, the firm does not provide any additional services or discounts to non-registered customers.

The registration form asks for a customer's demographics, contact information, and if they are a first-time Rx. cosmetics user. The registration form also asks three profiling questions regarding a customer's (i) skin type, (ii) skin problem, and (iii) product category of interest. A customer can choose to respond to any of these profiling questions; if they do, they receive personalized services such as product recommendations based on the responses they provide. These personalized services support their search process and reduce search effort to find the right products. The registration form has two sections. Although all fields in the first section must be filled out to place an order and complete a transaction, those in the second section including the three profiling questions are optional.

Whether a customer responds to these profiling questions is important in our study for the following reasons. First, it is clearly indicated in the registration form that responding to profiling questions is voluntary. Second, these profiling questions ask customers to reveal information related to their health conditions, which is often sensitive. The *Accenture Personalization Survey* reports that people are more concerned about revealing their health information than they are demographic and contact information [67]. Hence, a customer incurs significant privacy costs in responding to these profiling questions. Third, the search costs for a product like Rx. cosmetics are likely to be high for first-time Rx. cosmetics users because they lack the knowledge and experience required to evaluate the suitability of a particular product to their skin conditions. Further, a combination of products, not a single product, is often used to treat a skin problem, and this combination could differ between customers with similar symptoms. Hence, the customers' responses to these profiling questions that reveal their skin conditions could be used to significantly improve the firm's services – search supports – and reduce search costs.

Like many online commerce firms, the firm distributes marketing solicitations through email and text messages; yet, it provides customers an option to opt-out from these solicitations in the registration form. The firm also provides discount coupons to selected customers and a customer can earn one by actively participating in activities such as marketing campaigns and discussion forum on the website. A customer that receives or earns a discount coupon can use it during checkout for a discounted purchase price. The customer's shopping process at the website is shown in Figure 1.

<< Figure 1 >>

3.2. Data

The firm provided us the completed registration form of each customer that signed-up on their website between January 2007 and February 2009. For each customer, the variables included in the dataset are *demographic information* ($DEMO$) such as *age* (A), *gender* (G), and *marital status* (MS), whether they *responded to profiling question* $i \in \{1,2,3\}$ (PQ_i), whether they were a *first-time Rx. cosmetics user* (FU) when signing-up with the website, and whether they opted-out of the firm's *email list* (ML) and *text message list* (TL) for solicitations. About 20% of customers that signed-up on the website are non-first-time Rx. cosmetics users. The dataset also includes information about each customer's shopping history such as the *total number of visits* to the website (NV), the *total number of purchases* (NP), and whether *a discount coupon* was *redeemed* (*Coupon Redemption*: CR) when purchasing products during the time period of our study dataset.

Two main variables of interest in our study are $INFO \in \{PQ_1, PQ_2, PQ_3, ID, ED\}$ that captures the customer's information disclosing decision and CR that captures the customer's coupon redemption decision. PQ_i is a binary variable that is equal to 1 if a customer responded to profiling question i; and 0 otherwise. In our sample, 48% of customers responded to profiling question 1 (regarding their skin types), 58% to profiling question 2 (regarding their skin condition problems), and 55% to profiling question 3 (regarding the product categories that they are interested in). Using PQ_i, we derived two additional variables: the *information disclosing* (ID) and the *extent of disclosing* (ED). ID is a binary variable that is equal to 1 if a customer responded to at least one profiling question; and 0 otherwise. ED is an ordered discrete variable that refers to the number of profiling questions that each customer responded to. Overall, 60% of customers in our sample chose to respond to at least one profiling question and customers responded to, on average, 1.6 profiling questions. CR is a binary variable that is equal to 1 if a customer redeemed a discount coupon when purchasing products; and 0 otherwise. In our sample, 33% of customers redeemed a discount coupon when purchasing products after they received or earned it.

As the firm does not store information about non-registered customers, the dataset does not include any information about customers that purchased products without registration. Among 6,608 registered customers in the dataset, we include 3,382 customers that purchased at least one product (and did not cancel or return) in our analysis. Table 1 provides the description and summary statistics of the variables used for the analysis of our models.[2]

<< Table 1 >>

4. Structural Models

Using a discrete choice model, we first model the customer's information disclosing decision (i.e., whether a customer responds to the firm's profiling questions in stage 1 in Figure 1) that we label the *Information Disclosing Model* (IDM) and test H1 and H2; and, we model the customer's coupon redemption decision (i.e., whether a customer redeems a discount coupon when purchasing products in stage 3 after receiving or earning it in stage 2 in Figure 1) that we label the *Coupon Redemption Model* (CRM) and test H3 and H4.

4.1. Information Disclosing Model (IDM)

If a customer discloses information (i.e., responds to the firm's profiling questions), then their utility is written as

$$U_1 = X_1\beta + Z\gamma + \epsilon_1. \tag{1}$$

Otherwise, their utility is written as

$$U_0 = X_0\beta + Z\gamma + \epsilon_0. \tag{2}$$

The subscripts 1 and 0 denote information disclosure and nondisclosure, respectively. X_1 and X_0 are observable attributes that affect the choice of information disclosure and Z are the choice invariant components. The error terms ϵ_1 and ϵ_0 are unobservable attributes.

[2] The correlation matrix of these variables as well as the comparison of demographic and behavioral characteristics of customers between those that responded to at least one profiling question and others that did not; and, between those that redeemed a discount coupon when purchasing products and others that did not, are available from the authors.

Assuming that the indifferent customer discloses information, a customer discloses information if $U_1 \geq U_0$. Hence, from (1) and (2), we write the probability of a customer disclosing information y_I as

$$y_I = \Pr(U_1 \geq U_0) = \Pr(\epsilon \leq X\beta) = F_\epsilon(X\beta), \tag{3}$$

where $X = X_1 - X_0$ and $\epsilon = \epsilon_0 - \epsilon_1$.

As a dependent variable of the IDM, we use $INFO \in \{PQ_1, PQ_2, PQ_3, ID, ED\}$, one at a time. Since ED is an ordered discrete variable, the ordered choice model is used when ED is used as a dependent variable. The binary choice model discussed above can be easily extended to the ordered choice model [22].

Building on the models used in the privacy calculus literature (e.g., the heterogeneous search cost model in Koh et al. [35]), we include whether a customer opted-out from the firm's *email list* (ML) and *text message list* (TL) for solicitations and whether a customer was a *first-time Rx. cosmetics user* (FU) at the time of registration with the website as observable attributes that affect the choice of information disclosure.[3] In addition, we use a customer's *demographic information* ($DEMO$) such as *age* (A), *gender* (G), and *marital status* (MS) as control variables in the IDM. We specify the empirical form we use for $X\beta$ in equation (3) as

$$X\beta = \beta_0 + \beta_1\, ML + \beta_2\, TL + \beta_3\, FU + \beta_4\, DEMO. \tag{4}$$

There can be other variables such as socio-economic factors that affect a customer's information disclosing decision that we do not include in our model. However, as discussed by Cramer [12], it has been shown by Wooldridge [68] that for logit and probit estimations, "*omitted variable bias does not carry over to the effect of the regressor on the outcome*" (p1). As we discuss in Section 5, we use the logit and probit for the estimation of our models.

[3] A customer decides whether to respond to the profiling questions at the time of registration with the website also.

4.2. Coupon Redemption Model (CRM)

Let I define an index (latent) variable that measures the unobserved coupon proneness of a customer, where the customer is likely to seek and use a discount coupon if $I \geq K$, where K is a threshold. Building on the models used in the literature on coupon proneness [5, 6, 11, 46, 47, 65], we define

$$I = W\delta + u, \tag{5}$$

where W are observable characteristics of a customer that affect the customer's coupon proneness and u are unobservable attributes. We, then, write the probability of coupon redemption, y_C , as

$$y_C = \Pr(I \geq K) = \Pr(W\delta + u \geq K) = \Pr(u' \leq W\delta) = F_{u'}(W\delta), \tag{6}$$

where $u' = K - u$.

We use *Coupon Redemption* (CR) as the dependent variable of the CRM. Building on the models used in the literature on coupon proneness [5, 6, 47, 65], we include a customer's *demographic information* ($DEMO$), *total number of visits* to the website (NV), and *total number of purchases* (NP) as observable factors that affect the customer's coupon proneness.[4] In addition, we include $INFO \in \{PQ_1, PQ_2, PQ_3, ID, ED\}$, one at a time, as another observable factor that can possibly be associated with the customer's coupon proneness and test if and how the customer's information disclosing behavior is related to their coupon redemption behavior. We specify the empirical form we use for $W\delta$ in equation (6) as

$$W\delta = \delta_0 + \delta_1\, INFO + \delta_2\, NV + \delta_3\, NP + \delta_4\, DEMO. \tag{7}$$

[4] Some of these earlier studies on coupon proneness also include the customer's psychographic characteristics and the coupon attractiveness in their models. However, the relationship between the psychographic characteristics and the coupon redemption is found to be insignificant [46] and we believe the coupon attractiveness is relatively less relevant in our study because the firm only sells its own brand products on its website and uses only one type of discount coupons. Moreover, as we discussed in the earlier section, it has been shown in the literature (see [12, 68]) that for logit and probit estimations, "*omitted variable bias does not carry over to the effect of the regressor on the outcome*" [12] (p1).

5. Model Estimation and Results

The various functional forms for $F(\cdot)$ in equations (3) and (6) have been suggested in the literature [22]. These include the logistic distribution function (yielding the logit estimation) and the standard normal distribution function (yielding the probit estimation). Following the literature, we use both the logit and probit estimation techniques and estimate the IDM given in equations (3) and (4) and the CRM given in equations (6) and (7) using maximum likelihood estimation.

5.1. Estimation Results of the IDM

The estimation results of the IDM reported in Tables 2 and 3 support H1 and H2. The negative and significant coefficients for ML and TL suggest that customers that opted-out from the firm's email list and text message list for solicitations (i.e., customers with high privacy costs) are less likely to respond to the firm's profiling questions (support H1). The positive and significant coefficients for FU suggest that the first-time Rx. cosmetics users (i.e., customers that expect higher benefits from the search supports) are more likely to respond to the firm's profiling questions (support H2). These results likely confirm the privacy calculus perspective; that is, customers disclose information if the expected benefits they can get by disclosing information justify their privacy costs.

<< Table 2 >> and << Table 3 >>

5.2. Estimation Results of the CRM

The estimation results of the CRM reported in Tables 4 and 5 support H4 but not H3. The negative and significant coefficients for NV and NP suggest that customers that visit the website more frequently and purchase more products from the website (i.e., loyal customers) are less likely to seek and use a discount coupon (support H4).[5] The negative and significant coefficients for $INFO$ suggest that compared to those customers that do not respond to the firm's profiling questions, customers that

[5] The estimation results from customer's demographic information ($DEMO$) are also somewhat consistent with the findings of earlier studies. For instance, the estimation results suggest a negative relationship between age and coupon proneness; and, it is consistent with the findings of Teel et al. [59].

respond are less likely to seek and use a discount coupon (contradict H3). This result suggests that customers that disclose information are less likely to be coupon prone; hence, monetary benefits such as discount coupons may not work as an effective means to elicit information from customers.

<< Table 4 >> and << Table 5 >>

5.3. Moderating Effect of Age

The estimation results from the CRM that show an inverse relationship between customers' coupon redemption behavior and their information disclosing behavior are somewhat in line with the findings of Turow et al. [62]; however, it contradicts or partially contradicts the findings of earlier studies [23, 27, 70]. A plausible explanation for this contradictory result can be that the dataset used in our study covers a wider range of age groups. Our data includes 3,382 customers in the age range of 12 – 54 years old (see Figure 3), whereas those earlier studies use survey and experiment data collected from university students.

<< Figure 3 >>

To test if age moderates the relationship between customers' information disclosing behavior and their coupon redemption behavior, we revise the CRM (we label $RCRM_{Age}$) by including the interaction term, $INFO \times A$, where A is actual age in years in equation (7) as

$$W\delta' = \delta_0' + \delta_1' \, INFO + \delta_2' \, NV + \delta_3' \, NP + \delta_4' \, DEMO + \delta_5' INFO \times A.$$

We then estimate the $RCRM_{Age}$ using the same estimation technique that we used for the estimation of the CRM. The estimation results when $INFO = ID$ are reported in Table 6; and the estimation results when $INFO = PQ_1, PQ_2, PQ_3$, or ED are available from the authors. The interaction terms are consistently significant (except when $INFO = PQ_1$) and negative. This suggests that age may indeed negatively moderate the relationship between customers' information disclosing behavior and their coupon redemption behavior. Consistent with the findings of earlier studies, customers that respond to the firm's profiling questions are more likely to seek and use a discount coupon in the age group of 12 – 21 years old; however, in the age group of 22 – 54 years old, customers that respond to the firm's profiling questions are less likely to seek and use a discount coupon (see Figure 4). In the age group of 12 – 21 years old, customers that disclose information are likely to be coupon prone; hence, a firm may be able to elicit information from these customers by providing monetary benefits such as discount coupons. However, in the age group of 22 – 54 years old, customers that disclose information are not likely to be coupon prone; and hence, monetary benefits may not work as an effective means to elicit information from these customers.

<< Table 6 >> and << Figure 4 >>

6. Robustness Check

Our interpretation of the estimation results from the CRM that shows an inverse relationship between customers' information disclosing behavior and their coupon redemption behavior is that, on average, customers that disclose information are less likely to be coupon prone; hence, a firm may not be able to elicit information from customers simply by providing monetary benefits such as discount coupons. However, there can be alternative interpretations. First, it is possible that customers with less serious skin condition problems have more incentive to respond to the firm's profiling questions as they are less knowledgeable about different types of Rx. cosmetics available in the market; yet, they do not have sufficient incentive to seek and use a discount coupon because the type of Rx. cosmetics that can treat their condition is less expensive. Second, it is also possible that some customers respond to the firm's profiling questions yet do not seek and use a discount coupon simply because they are less experienced with online shopping.

To test these two alternative interpretations, we revise the IDM (we label the $\text{RIDM}_{\text{Alter}}$) and the CRM (we label the $\text{RCRM}_{\text{Alter}}$) by including the *average transaction value* (ATV) as a proxy measure for the seriousness of skin problems, and the *online shopping experience* (OSE) as a proxy measure for the level of experience with online shopping of each customer in equations (4) and (7).

ATV refers to the dollar amount that each customer spent on the website in each transaction. On average, customers in our sample spent about \$50USD in each transaction (*min* is \$8.5USD and *max* is \$382.5USD). For a non-first-time Rx. cosmetics user, the registration form asks where they purchased Rx. cosmetic products before (i.e., before singing-up with the website in stage 1 in Figure 1): other online commerce website, TV shopping channel, or dermatology clinic. OSE is a binary variable that is equal to 1 if a customer chose other online commerce website; and 0 otherwise. Among those non-first-time Rx. cosmetics users in our sample, about 10% chose other online commerce website; 25% and 8% chose TV shopping channel and dermatology clinic, respectively; and, the remaining 57% indicated that they used a Rx. cosmetics product that their friends or family had (before signing-up with the website). We also include the interaction terms $INFO \times ATV$ and $INFO \times OSE$ in equation (7) and test the moderating effects of ATV and OSE on the relationship between customers' information disclosing and their coupon redemption behaviors.

We estimate the $\text{RIDM}_{\text{Alter}}$ and the $\text{RCRM}_{\text{Alter}}$ using the same estimation technique that we used for the estimation of our base models (discussed in Section 5). Tables 7 and 8 report the estimation results of the $\text{RIDM}_{\text{Alter}}$ when ID is used as a dependent variable; and, Tables 9 and 10 report the estimation results of the $\text{RCRM}_{\text{Alter}}$ when $INFO = ID$. The estimation results when PQ_1, PQ_2, PQ_3, or ED is used as a dependent variable for the $\text{RIDM}_{\text{Alter}}$ and when $INFO = PQ_1$, PQ_2, PQ_3, or ED for the $\text{RCRM}_{\text{Alter}}$ are qualitatively identical to those reported in Tables 7 – 10; and, are available from the authors upon request.

The estimation results reported in Tables 7 – 10 reject the alternative interpretations. The significant and positive coefficients for ATV in Tables 7 and 8 suggest that customers that have more serious skin problems (i.e., that spend more money in each transaction on the website) are more likely to respond to the firm's profiling questions; however, perhaps surprisingly, the significant and negative coefficients for ATV in Tables 9 and 10 suggest that they are less likely to seek and use a discount coupon (although they spend more money in each transaction on the website). The insignificant coefficients for OSE in all tables suggest that a customer's online shopping experience does not likely have a significant impact on their information disclosing decision and their coupon redemption decision.

These additional results show that our main findings hold even after accounting for the seriousness of a customer's skin problems and their experience with online shopping. Consistent with the estimation results from our base models (the IDM and the CRM), although customers that opt-out from the firm's email and text message lists for solicitations (those that likely have high privacy costs) are less likely to respond to the firm's profiling questions, the first-time Rx. cosmetics users (those that likely expect more reduction in search costs from the personalized services that the firm provides using the information that customers disclose) are more likely to respond to the firm's profiling questions (see Tables 7 and 8). Compared to those customers that do not respond to the firm's profiling questions, customers that respond to the firm's profiling questions are, on average, less likely to seek and use a discount coupon (see Tables 9 and 10).

<< Table 7 >> and << Table 8 >> and << Table 9 >> and << Table 10 >>

7. Discussion and Conclusion

Using the data collected from the firm that sells Rx. cosmetics on its website, we confirmed that customers' actual information disclosing behavior are based on the tradeoff between their privacy costs and the expected benefits of disclosing information. Further, we found that customers, on average, are not likely to disclose information simply as a tradeoff for monetary benefits. Monetary benefits may work as an effective means to elicit information but most likely only from customers in the age range of 12 – 21 years old. The personalized services such as product recommendations which are directly tied to the information that customers disclose outweigh the monetary benefits such as discount coupons or cash rewards in enticing customers to disclose information.

Many existing studies on customers' information disclosing behavior rely on survey or experiment data and their results are based on customers' intentions. In contrast, our study uses actual transaction data, and hence, the results are based on true utility-maximizing behavior. Furthermore, our data allows us to investigate the relationship between customers' information disclosing behavior and their coupon redemption behavior, which hitherto has not been empirically examined in-depth.

Our data, however, has some limitations. First, because it is actual transaction data, it does not have direct measures for customers' privacy costs and the expected benefits from the firm's personalized services; hence, we rely on proxy measures. Although it is noted in Smith et al. [56] that measuring privacy is nearly impossible, it would be worthwhile to look for direct measures and to verify our results. Second, since our dataset does not include any information about non-registered customers, the results of our study could be biased toward those that have less privacy concerns. Third, the coupon attractiveness is another factor that can affect the probability of coupon redemption [6]. However, we do not have the detailed characteristics of coupons that each customer used. Consequently, we cannot assess the coupon attractiveness offered by the firm in our study relative to other online coupons. Lastly, although we provide important implications for academics and practitioners regarding customers' information disclosing behavior, our results provide limited insights for customers. Ghose [21] argues that because the firms can better customize their ads, customers receive fewer irrelevant ads if they disclose more information. Paradoxically, customers could reduce their privacy costs in the sense of irrelevant ads by disclosing more information. However, Koh et al. [35] show that a reduction in privacy costs does not always benefit customers and society under voluntary profiling if the firms use customer information for personalized pricing (i.e., for their coupon distribution strategies). It would be valuable to extend our model and empirically investigate if customers can reduce their privacy costs by providing more information, given that the firm can use the information for the personalized pricing.

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Tables and Figures

Table 1. Descriptive statistics of the variables used for the analysis of our models

Variables	Mean	Min	Max
Response to profiling question 1 (PQ_1) *1=Responded to profiling question 1; 0=Otherwise*	0.48	0	1
Response to profiling question 2 (PQ_2) *1=Responded to profiling question 2; 0=Otherwise*	0.58	0	1
Response to profiling question 3 (PQ_3) *1=Responded to profiling question 3; 0=Otherwise*	0.55	0	1
Information disclosing (ID) *1=Responded to at least one profiling question; 0=Otherwise*	0.60	0	1
Extent of disclosing (ED)	1.61	0	3
Coupon redemption (CR) *1=Redeemed a discount coupon when purchasing products; 0=Otherwise*	0.33	0	1
Email list (ML) *1=Opted-out from the firm's email list for solicitations; 0=Otherwise*	0.16	0	1
Text message list (TL) *1=Opted-out from the firm's text message list for solicitations; 0=Otherwise*	0.23	0	1
First-time Rx. cosmetics user (FU) *1=First-time Rx. cosmetics user; 0=Otherwise*	0.81	0	1
Total number of visits to the website (NV)	4.67	1	104
Total number of purchases (NP)	1.75	1	38
Age (A)	28.49	12	54
Gender (G) *1=Male; 0=Female*	0.27	0	1
Marital status (MS) *1=Married; 0=Single*	0.12	0	1

Table 2. Estimation results of the IDM using the logit model

IDM	$y_I = PQ_1$	$y_I = PQ_2$	$y_I = PQ_3$	$y_I = ID$	$y_I = ED$
Email list (ML)	-0.4643***	-0.5882***	-0.6190***	-0.5599***	-0.5424***
1=Opt-out; 0=Otherwise	(0.1088)	(0.1066)	(0.1062)	(0.1064)	(0.0989)
Text message list (TL)	-0.1845**	-0.2595***	-0.2240**	-0.2713***	-0.2233***
1=Opt-out; 0=Otherwise	(0.0930)	(0.0920)	(0.0912)	(0.0921)	(0.0854)
First-time Rx. cosmetics user (FU)	0.1823*	0.2063**	0.1701*	0.1898**	0.1781**
1=First-time user; 0=Otherwise	(0.0958)	(0.0951)	(0.0939)	(0.0955)	(0.0874)
Age (A)	-0.0594***	-0.0556***	-0.0489***	-0.0495***	-0.0530***
	(0.0065)	(0.0063)	(0.0062)	(0.0063)	(0.0057)
Gender (G)	-0.0100	0.0220	-0.1071	0.0457	-0.0448
1=Male; 0=Female	(0.0838)	(0.0841)	(0.0832)	(0.0844)	(0.0773)
Marital status (MS)	3.3464***	3.6647***	3.0256***	4.1144***	2.8751***
1=Married; 0=Single	(0.2030)	(0.2700)	(0.2102)	(0.3479)	(0.1640)
Constant 1	1.2808***	1.6173***	1.3955***	1.5309***	1.6711***
	(0.2054)	(0.2037)	(0.2000)	(0.2034)	(0.1868)
Constant 2					0.1507***
					(0.0141)
Constant 3					0.6589***
					(0.0280)
χ^2	519.27***	485.82***	430.39***	468.39***	518.59***

Note: $N = 3{,}382$; Standard errors are in parentheses; $^{*}\ p \leq 0.1$, $^{**}\ p \leq 0.05$, $^{***}\ p \leq 0.01$

Table 3. Estimation results of the IDM using the probit model

IDM	$y_I = PQ_1$	$y_I = PQ_2$	$y_I = PQ_3$	$y_I = ID$	$y_I = ED$
Email list (ML)	-0.2784***	-0.3586***	-0.3810***	-0.3460***	-0.3328***
1=Opt-out; 0=Otherwise	(0.0660)	(0.0654)	(0.0650)	(0.0655)	(0.0606)
Text message list (TL)	-0.1110*	-0.1578***	-0.1339**	-0.1652***	-0.1323**
1=Opt-out; 0=Otherwise	(0.0568)	(0.0568)	(0.0563)	(0.0570)	(0.0525)
First-time Rx. cosmetics user (FU)	0.1072*	0.1266**	0.1025*	0.1148*	0.1079**
1=First-time user; 0=Otherwise	(0.0582)	(0.0583)	(0.0576)	(0.0587)	(0.0535)
Age (A)	-0.0358***	-0.0340***	-0.0299***	-0.0304***	-0.0324***
	(0.0038)	(0.0038)	(0.0037)	(0.0038)	(0.0035)
Gender (G)	-0.0043	0.0163	-0.0678	0.0312	-0.0260
1=Male; 0=Female	(0.0515)	(0.0519)	(0.0513)	(0.0521)	(0.0476)
Marital status (MS)	1.9408***	2.0480***	1.7425***	2.2305***	1.7514***
1=Married; 0=Single	(0.1038)	(0.1271)	(0.1067)	(0.1519)	(0.0897)
Constant 1	0.7664***	0.9895***	0.8546***	0.9435***	1.0224***
	(0.1235)	(0.1238)	(0.1217)	(0.1242)	(0.1134)
Constant 2					0.0933***
					(0.0087)
Constant 3					0.4070***
					(0.0172)
χ^2	517.21***	485.16***	429.93***	486.60***	529.74***

Note: $N = 3{,}382$; Standard errors are in parentheses; $^{*}\ p \leq 0.1$, $^{**}\ p \leq 0.05$, $^{***}\ p \leq 0.01$

Table 4. Estimation results of the CRM using the logit model

CRM ($y_C = CR$)	$INFO = PQ_1$	$INFO = PQ_2$	$INFO = PQ_3$	$INFO = ID$	$INFO = ED$
Information disclosing decision ($INFO$)	-0.0491	-0.1502*	-0.2142***	-0.1426*	-0.0532*
	(0.0791)	(0.0789)	(0.0782)	(0.0792)	(0.0282)
Number of visits to the website (NV)	-0.0161*	-0.0155*	-0.0154*	-0.0156*	-0.0157*
	(0.0089)	(0.0089)	(0.0089)	(0.0089)	(0.0089)
Number of purchases (NP)	-0.1281***	-0.1280***	-0.1280***	-0.1279***	-0.1283***
	(0.0360)	(0.0360)	(0.0360)	(0.0360)	(0.0360)
Age (A)	-0.0292***	-0.0303***	-0.0308***	-0.0300***	-0.0304***
	(0.0062)	(0.0062)	(0.0062)	(0.0062)	(0.0062)
Gender (G)	0.1909**	0.1907**	0.1843**	0.1915**	0.1890**
1=Male; 0=Female	(0.0841)	(0.0841)	(0.0842)	(0.0841)	(0.0841)
Marital status (MS)	0.0385	0.0891	0.1186	0.0837	0.0964
1=Married; 0=Single	(0.1377)	(0.1361)	(0.1356)	(0.1359)	(0.1375)
Constant	0.3447*	0.4289**	0.4723**	0.4205**	0.4315**
	(0.1894)	(0.1908)	(0.1898)	(0.1905)	(0.1915)
χ^2	86.87***	90.11***	94.00***	89.72***	90.05***

Note: $N = 3{,}382$; Standard errors are in parentheses; * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 5. Estimation results of the CRM using the probit model

CRM ($y_C = CR$)	$INFO = PQ_1$	$INFO = PQ_2$	$INFO = PQ_3$	$INFO = ID$	$INFO = ED$
Information disclosing decision ($INFO$)	-0.0295	-0.0935*	-0.1321***	-0.0887*	-0.0329*
	(0.0482)	(0.0482)	(0.0476)	(0.0483)	(0.0172)
Number of visits to the website (NV)	-0.0093*	-0.0089*	-0.0088*	-0.0090*	-0.0090*
	(0.0051)	(0.0050)	(0.0051)	(0.0050)	(0.0051)
Number of purchases (NP)	-0.0767***	-0.0767***	-0.0767***	-0.0767***	-0.0769***
	(0.0205)	(0.0205)	(0.0205)	(0.0205)	(0.0205)
Age (A)	-0.0173***	-0.0181***	-0.0184***	-0.0179***	-0.0181***
	(0.0034)	(0.0037)	(0.0037)	(0.0037)	(0.0037)
Gender (G)	0.1171**	0.1170**	0.1129**	0.1174**	0.1159**
1=Male; 0=Female	(0.0515)	(0.0516)	(0.0516)	(0.0515)	(0.0516)
Marital status (MS)	0.0237	0.0561	0.0735	0.0527	0.0600
1=Married; 0=Single	(0.0826)	(0.0817)	(0.0813)	(0.0816)	(0.0825)
Constant	0.1860	0.2405**	0.2667**	0.2351**	0.2410**
	(0.1135)	(0.1146)	(0.1139)	(0.1144)	(0.1150)
χ^2	87.19***	90.59***	94.51***	90.19***	90.48***

Note: $N = 3{,}382$; Standard errors are in parentheses; * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 6. Estimation results of the RCRM

$y_C = CR$ & $INFO = ID$	CRM		$RCRM_{Age}$	
	Logit	**Probit**	**Logit**	**Probit**
Information disclosing decision ($INFO$)	-0.1426*	-0.0887*	0.5849*	0.3400*
	(0.0792)	(0.0483)	(0.3364)	(0.2022)
Number of visits to the website (NV)	-0.0156*	-0.0090*	-0.0161*	-0.0092*
	(0.0089)	(0.0050)	(0.0089)	(0.0051)
Number of purchases (NP)	-0.1279***	-0.0767***	-0.1256***	-0.0755***
	(0.0360)	(0.0205)	(0.0359)	(0.0205)
Age (A)	-0.0300***	-0.0179***	-0.0158*	-0.0094*
	(0.0062)	(0.0037)	(0.0088)	(0.0053)
Gender (G)	0.1915**	0.1174**	0.1961**	0.1203**
1=Male; 0=Female	(0.0841)	(0.0515)	(0.0842)	(0.0516)
Marital status (MS)	0.0837	0.0527	0.1855	0.1133
1=Married; 0=Single	(0.1359)	(0.0816)	(0.1438)	(0.0862)
Information disclosing decision × Age ($INFO \times A$)			-0.0266**	-0.0156**
			(0.0120)	(0.0071)
Constant	0.4205**	0.2351**	0.0144	-0.0068
	(0.1905)	(0.1144)	(0.2621)	(0.1589)
χ^2	89.72***	90.19***	94.68***	94.95***

Note: $N = 3{,}382$; Standard errors are in parentheses; * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 7. Estimation results of the $RIDM_{Alter}$ using the logit model

$y_I = ID$	IDM	$RIDM_{Alter}$		
		(1)	**(2)**	**(3)**
Email list (ML)	-0.5599***	-0.5469***	-0.5621***	-0.5491***
1=Opt-out; 0=Otherwise	(0.1064)	(0.1066)	(0.1065)	(0.1066)
Text message list (TL)	-0.2713***	-0.2658***	-0.2707***	-0.2652***
1=Opt-out; 0=Otherwise	(0.0921)	(0.0923)	(0.0922)	(0.0923)
First-time Rx. cosmetics user (FU)	0.1898**	0.2074**	0.2169**	0.2352**
1=First-time user; 0=Otherwise	(0.0955)	(0.0958)	(0.0994)	(0.0998)
Age (A)	-0.0495***	-0.0522***	-0.0495***	-0.0523***
	(0.0063)	(0.0064)	(0.0063)	(0.0064)
Gender (G)	0.0457	0.0592	0.0453	0.0587
1=Male; 0=Female	(0.0844)	(0.0847)	(0.0844)	(0.0847)
Marital status (MS)	4.1144***	4.1177***	4.1150***	4.1182***
1=Married; 0=Single	(0.3479)	(0.3481)	(0.3479)	(0.3481)
Average Transaction value (ATV)		0.3239***		0.3248***
		(0.1192)		(0.1192)
Online shopping experience (OSE)			0.2833	0.2892
			(0.2924)	(0.2925)
Constant	1.5309***	1.4250***	1.5602***	1.3995***
	(0.2034)	(0.2072)	(0.2050)	(0.2088)
χ^2	468.39***	493.95***	487.34***	494.93***

Note: $N = 3{,}382$; Standard errors are in parentheses; * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 8. Estimation results of the $\text{RIDM}_{\text{Alter}}$ using the probit model

$\boldsymbol{y_I = ID}$	**IDM**	**$\text{RIDM}_{\text{Alter}}$**		
		(1)	**(2)**	**(3)**
Email list (ML)	-0.3460***	-0.3379***	-0.3472***	-0.3392***
1=Opt-out; 0=Otherwise	(0.0655)	(0.0656)	(0.0655)	(0.0656)
Text message list (TL)	-0.1652***	-0.1613***	-0.1649***	-0.1610***
1=Opt-out; 0=Otherwise	(0.0570)	(0.0570)	(0.0570)	(0.0570)
First-time Rx. cosmetics user (FU)	0.1148*	0.1264**	0.1320**	0.1441**
1=First-time user; 0=Otherwise	(0.0587)	(0.0589)	(0.0612)	(0.0614)
Age (A)	-0.0304***	-0.0321***	-0.0305***	-0.0321***
	(0.0038)	(0.0039)	(0.0038)	(0.0039)
Gender (G)	0.0312	0.0392	0.0310	0.0389
1=Male; 0=Female	(0.0521)	(0.0523)	(0.0521)	(0.0523)
Marital status (MS)	2.2305***	2.2316***	2.2316***	2.2328***
1=Married; 0=Single	(0.1519)	(0.1520)	(0.1520)	(0.1521)
Average Transaction value (ATV)		0.1930***		0.1937***
		(0.0715)		(0.0715)
Online shopping experience (OSE)			0.1779	0.1816
			(0.1786)	(0.1784)
Constant	0.9435***	0.8799***	0.9280***	0.8638***
	(0.1242)	(0.1266)	(0.1252)	(0.1275)
χ^2	486.60***	493.92***	487.59***	494.96***

Note: $N = 3{,}382$; Standard errors are in parentheses; * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

Table 9. Estimation results of the $\text{RCRM}_{\text{Alter}}$ using the logit model

$\boldsymbol{y_C = CR}$ **&** $\boldsymbol{INFO = ID}$	**CRM**	$\textbf{RCRM}_{\textbf{Alter}}$		
		(1)	**(2)**	**(3)**
Information disclosing decision ($INFO$)	-0.1426* (0.0792)	-0.3371* (0.1750)	-0.1506* (0.0799)	-0.3410* (0.1752)
Number of visits to the website (NV)	-0.0156* (0.0089)	0.0045 (0.0086)	-0.0157* (0.0089)	0.0045 (0.0086)
Number of purchases (NP)	-0.1279*** (0.0360)	-0.1331*** (0.0362)	-0.1281*** (0.0360)	-0.1330*** (0.0362)
Age (A)	-0.0300*** (0.0062)	-0.0097 (0.0065)	-0.0303*** (0.0062)	-0.0098 (0.0065)
Gender (G) *1=Male; 0=Female*	0.1915** (0.0841)	0.0952 (0.0883)	0.1902** (0.0842)	0.0939 (0.0883)
Marital status (MS) *1=Married; 0=Single*	0.0837 (0.1359)	0.0968 (0.1432)	0.0818 (0.1360)	0.0953 (0.1432)
Average Transaction value (ATV)		-3.4654*** (0.3212)		-3.4707*** (0.3214)
$INFO \times ATV$		0.6798*** (0.3956)		0.6864* (0.3957)
Online shopping experience (OSE)			-0.1216 (0.4390)	0.2152 (0.4800)
$INFO \times OSE$			0.4356 (0.5585)	0.0530 (0.6043)
Constant	0.4205** (0.1905)	1.2663*** (0.2268)	0.4303** (0.1909)	1.2687*** (0.2270)
χ^2	89.72***	450.45***	90.61***	481.18***

Note: $N = 3{,}382$; Standard errors are in parentheses; $^{*}\ p \leq 0.1$, $^{**}\ p \leq 0.05$, $^{***}\ p \leq 0.01$

Table 10. Estimation results of the $RCRM_{Alter}$ using the probit model

$y_C = CR$ & $INFO = ID$	CRM	$RCRM_{Alter}$ (1)	$RCRM_{Alter}$ (2)	$RCRM_{Alter}$ (3)
Information disclosing decision ($INFO$)	-0.0887*	-0.1660*	-0.0935*	-0.1683*
	(0.0483)	(0.0932)	(0.0487)	(0.0933)
Number of visits to the website (NV)	-0.0090*	0.0027	-0.0090*	0.0027
	(0.0050)	(0.0049)	(0.0051)	(0.0049)
Number of purchases (NP)	-0.0767***	-0.0847***	-0.0768***	-0.0848***
	(0.0205)	(0.0204)	(0.0205)	(0.0204)
Age (A)	-0.0179***	-0.0064*	-0.0180***	-0.0065*
	(0.0037)	(0.0039)	(0.0037)	(0.0039)
Gender (G)	0.1174**	0.0629	0.1167**	0.0621
1=Male; 0=Female	(0.0515)	(0.0533)	(0.0516)	(0.0533)
Marital status (MS)	0.0527	0.0569	0.0514	0.0558
1=Married; 0=Single	(0.0816)	(0.0844)	(0.0816)	(0.0844)
Average Transaction value (ATV)		-1.6335***		-1.6344***
		(0.1451)		(0.1452)
$INFO \times ATV$		0.2756		0.2768
		(0.1808)		(0.1809)
Online shopping experience (OSE)			-0.0783	0.0762
			(0.2683)	(0.2858)
$INFO \times OSE$			0.2648	0.0927
			(0.3415)	(0.3604)
Constant	0.2351**	0.6180***	0.2411**	0.6203***
	(0.1144)	(0.1298)	(0.1147)	(0.1299)
χ^2	90.19***	405.26***	91.04***	405.92***

Note: $N = 3{,}382$; Standard errors are in parentheses; * $p \leq 0.1$, ** $p \leq 0.05$, *** $p \leq 0.01$

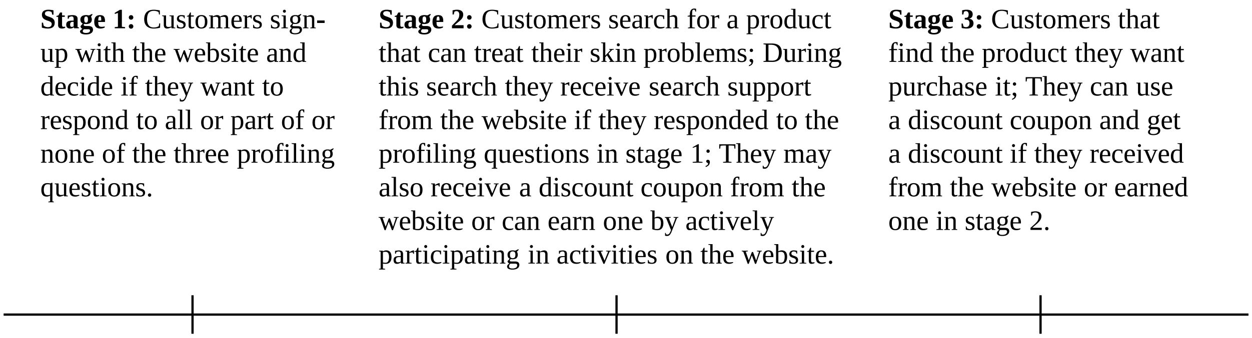

Figure 1. The customer's shopping process at the firm's online commerce website

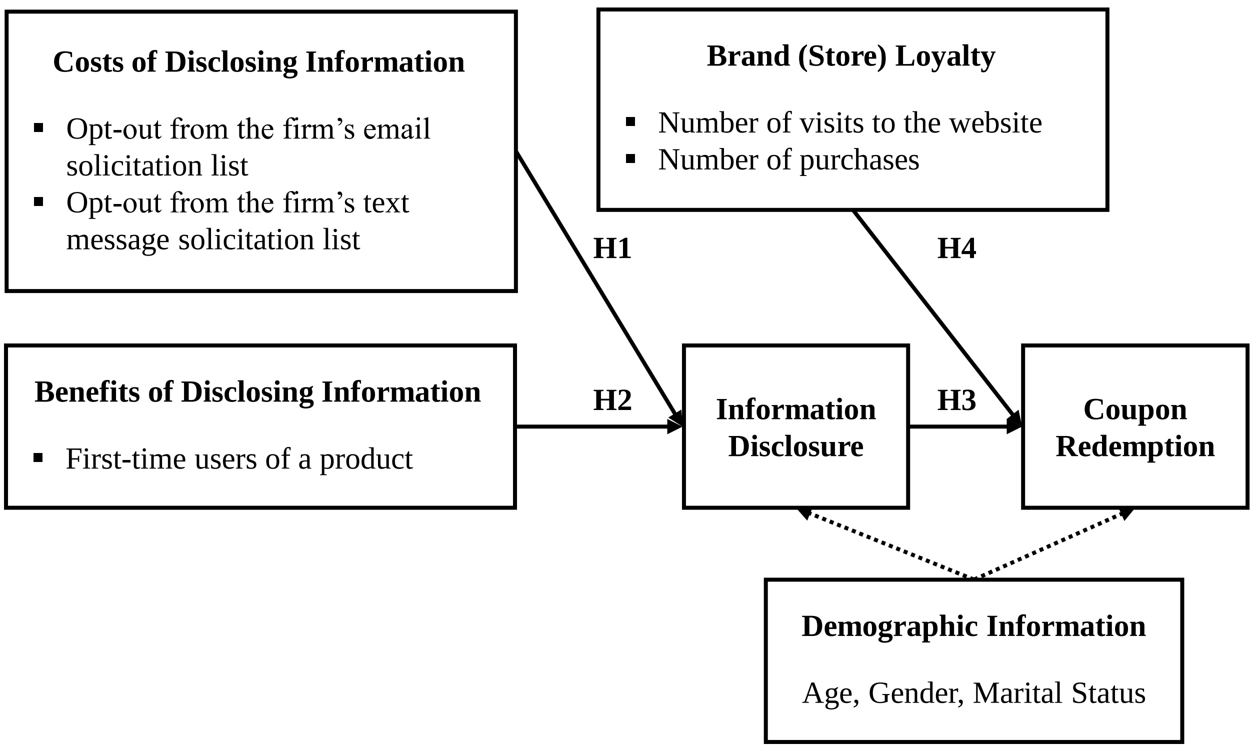

Figure 2. The summary of hypotheses

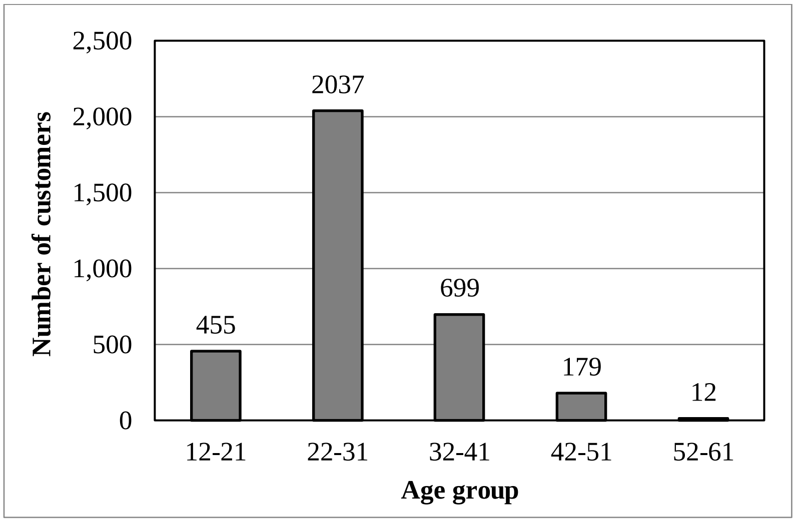

Figure 3. The age distribution of customers in our sample

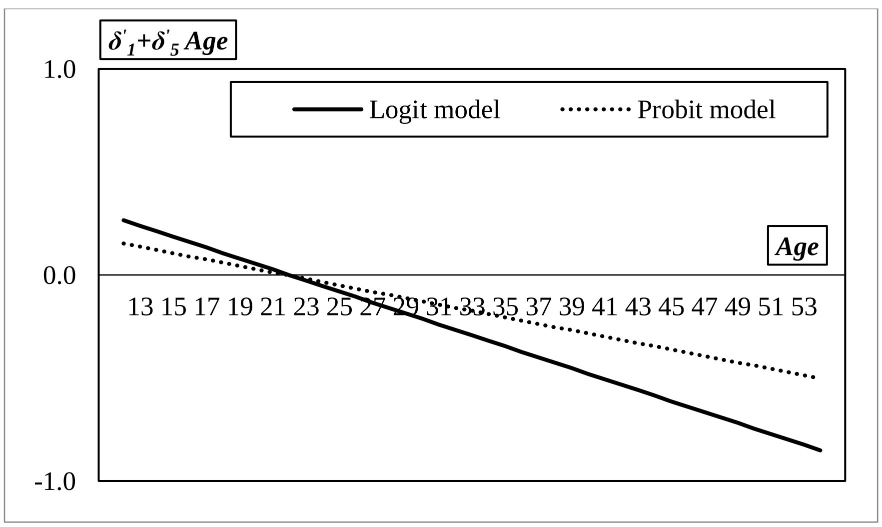

Figure 4. The moderating effect of age on the relationship between customers' information disclosing behavior and their coupon redemption behavior