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Abstract

This dissertation consists of three essays related to the economics of personalization of information goods such as web content, mobile services and online advertising. Today's online consumers are simply overwhelmed by the amount of information they have to deal with -- the majority of which is often irrelevant to their needs and interests. This unfiltered flood of information results in an unpleasant online experience for consumers -- and one that fails to generate the maximum possible product purchases, content or ad clicks, and return visits. Improving the online experience requires changing the way websites approach online content. To achieve this, firms are revisiting personalization -- a technology that came to the forefront in the late 1990s but suffered a severe backlash with the bursting of the dot-com bubble.

While personalization is an important technology in ecommerce, there is not much prior work on the economics of personalization in case of information goods and services. In this dissertation, I use mathematical tools (mainly Game Theory, Classical and Bayesian Econometrics) to investigate the economic, managerial and policy issues when firms implement personalization In my first two essays, I use analytical models based on horizontal and vertical product differentiation to understand how internet personalization affects quality, pricing, information sharing and consumer surplus in a market. I also explore how the impact of personalization is mediated by microeconomic variables such as market structure and information ownership. In my third essay, I measure the tradeoff between personalization and privacy by building and empirically testing a conceptual model of how consumers respond to firms’ collection and use of information for personalization. A brief description of my research is as follows:

Essay 1: Personalization in a Two Dimensional Product Differentiation Model: Impact of Market Structure and the Q-F Ratio

In this essay, we examine the economics of personalization in the case of information goods and services. We extend prior work in this area in several ways: one, we consider a more general two dimensional duopoly model of product differentiation where consumers attach different levels of importance to various product attributes. Two, we allow for imperfect personalization in our model and consider how improvements in personalization technologies impact the equilibrium. Finally, we examine different market structures based on the locational differentiation and examine how firms’ ex-ante location impacts equilibrium with or without personalization. We report the equilibrium in terms of the ‘Quality-Fit’ (Q-F) Ratio, which measures the relative strength of consumer preferences on each dimension of product differentiation.

Our main results are as follows: Personalization is not always profitable for a firm. When firms are ex-ante horizontally differentiated, personalization is profitable only for high values of the Q-F Ratio. However, under some conditions, a firm might find it profitable to personalize for low Q-F values if the effectiveness of the technology is high. On the other hand, if firms are ex-ante vertically differentiated, personalization by one firm can lead to higher profits for both firms if the Q-F ratio is low. Another interesting result is that consumer surplus does not always increase when a firm adopts personalization. Personalization can lead to an increase or decrease in consumer surplus depending on the Q-F Ratio and the market structure. Finally, we also examine how the equilibrium quality levels change with personalization adoption. We find that personalization adoption leads to increased quality differentiation between firms.
when ex-ante, firms are horizontally differentiated and the \( Q-F \) Ratio is low. In other cases, personalization leads to reduction in vertical differentiation between firms. In other words, personalization and quality can be complements or substitutes depending on the \( Q-F \) Ratio and the market structure. Our research also sheds light on equilibriums in two-dimensional product differentiation models and shows that, given exogenous location choice, personalization can lead to MaxMax and MinMin equilibriums (in addition to the standard MaxMin result).

**Essay 2: Personalization, Information Sharing and Privacy – An Analytical Perspective**

Advances in information technology and access to huge volumes of consumer information enable firms to offer personalized products to customers. Conventional wisdom dictates that direct marketers should zealously guard all information about their consumers. However, the truth is that many direct marketers routinely share customer information with one another (Chen et al 2001). In this paper, we present a simple economic model to analyze the equilibrium in a market where firms share consumer information with one another, when this information can be used to offer personalized products. We also analyze issues such as optimal scope of personalization, different information ownership scenarios and the presence of privacy conscious consumers.

We show that even when the marginal cost of personalization is low, offering a personalized product only to high valuation customers is a weakly dominating strategy compared to offering a personalized product to all customers in the market. We also show that information sharing between firms can lead to a tacit collusion equilibrium where both firms charge higher prices and earn higher profits than when there is no information sharing. However, information sharing by firms can also lead to an increase in consumer welfare under some conditions. We also show that giving consumers ownership rights to their information does not preclude the existence of information sharing mechanisms. Under different conditions, information ownership by consumers poses a non-credible threat, when select consumers who are better off after information sharing allow their information to be shared even if all other consumers are worse off after information sharing or a credible threat when information ownership by consumers deters firms from sharing information. Finally, our study shows that presence of privacy sensitive customers can actually benefit firms under some conditions.

**Essay 3: Examining the Personalization-Privacy Tradeoff – an Empirical Investigation with Email Advertisements**

Dale Carnegie once said that the sound of one’s name is the sweetest for any person. Much internet personalization acts on this mantra by trying to create an online environment where customers are greeted by name and are recommended products based on their preferences. However, no clear empirical evidence exists as to how consumers actually respond when firms use their information to offer a personalized product. Using theories from psychology and consumer behavior, we address this dilemma by developing hypotheses related to consumers’ response to a firm’s collection and use of information for personalization. To test these hypotheses, we propose a multi-stage ordered probit model using a hierarchical Bayesian framework to account for consumer heterogeneity via individual level parameter estimates. The data for this research comes from a website which captured information on actual consumer responses to ten million email advertisements sent to 600,000 customers over a nine month period. We examine the impact of different types of personalization as well as measure consumer response at multiple levels. We also control for consumer and promotion specific characteristics in our model.
Our results not only indicate the economic benefits of personalization but also highlight consumers’ privacy concerns. The main results are as follows: first, emails personalized only on the basis of consumers’ product preferences get a more favorable response from consumers than those with no personalization. Second, we show that more than 85% consumers react negatively to personalized greetings in an email, suggesting that consumers are likely to perceive a violation in privacy if they see their name in an email advertisement. Third, we show that consumer response is mixed if both personalized greetings and product-based personalization are used in an email. While most consumers react negatively if both personalized greetings and product-based personalization are used in an email, consumers who buy more often from a firm prefer emails where personalized greetings are accompanied by reliable product recommendations. This suggests that familiarity with a website mitigates customers’ privacy concerns. Overall, we show that customers differ significantly in their preference for different types of personalization and that ‘personalized’ personalization (where different customers receive different levels of personalization) is more effective than all-inclusive personalization (in which each advertisement is personalized at multiple levels).
Essay 1: Personalization in a Two Dimensional Product Differentiation Model: Impact of Market Structure and the Q-F Ratio

1. Introduction and Literature Review

Personalization, also known as ‘One-to One Marketing’ (Peppers and Rogers, 1996), refers to the practice of using information technology to treat customers on an individual basis by tailoring products, customer service and other interactions uniquely for each customer. Personalization is a broad term and includes the following practices:

- Addressing customers by name and remembering their preferences.
- Showing customers specific content based on who they are and their past behavior (online recommendations – e.g. amazon.com).
- Allowing visitors to customize a site / product for their specific purposes (customization – e.g. mywashingtonpost.com, reflect.com)
- Targeting advertisements based on customer information (e.g. doubleclick.com, yesmail.com)

In this research, we consider personalization in the context of online information. Information personalization is widely used by firms in two ways: one, personalization of information goods (i.e. when information itself is the product such as online content, mobile services etc); two, personalization of information-related attributes of physical goods (i.e., when the information is auxiliary to the product as in case of amazon.com which sells books, but also uses consumer information to create a personalized experience for shoppers by giving online recommendations, one-click checkout etc).

Personalization of information is a fast growing practice among firms. The information age and the ubiquity of the internet have ushered an overload of information. On the internet, this information overload is created by the proliferation of numerous websites, as well as the increase in links and sub-links within each website. For example, a medium-sized travel portal (iExplore.com) reported more than 50,000 pages of

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1 Many people confuse personalization with customization. Customization is a static version of personalization in the sense that in customization, the firm does not update the customer profile automatically; the updating of the user profile takes place when the user explicitly changes the interface at some point of time. Personalization, on the other hand, is a broader term because it uses information provided explicitly by the customer, as well as information gathered about the customer through observing browsing behavior or obtaining information from third party sources. Montgomery et al (2003) cite a few problems in using pure customization, e.g., customers may not give right answers, they may not know the right answers or may not be willing to answer at all.
dynamic content, including 1,056 separate trips for hiking, trekking, and walking. Consumers have a wide variety of preferences and it can be very difficult and time-consuming for a customer to search through and evaluate all these options to locate her ideal product. To resolve this issue, iExplore has implemented a personalization solution from ATG to deliver content to site visitors based on their particular interests, helping customers find what they need with fewer clicks and in less time. Personalization is not only restricted to information goods. Even firms which sell non-customizable physical goods (e.g. books, apparel) or services (e.g. credit cards, financial services) can create a personalized experience for their customers by tailoring the non-product information-related attributes. However, not all firms have been successful with personalization. In a survey, Jupiter Research reported that only 8% of consumers said that personalization prompted repeat visits to content, news, or entertainment websites. Firms such as Go and AltaVista have publicly scaled back their personalization efforts. The personalization industry seems to be in a flux with many vendors either closing shop or merging with other players. The main research question we address is: what is the impact of personalization on firm profitability? In other words, under what market conditions does a firm find it profitable to implement personalization? Also, how does personalization impact the consumer surplus, i.e., are consumers always better off when a firm adopts personalization?

1.1 Personalization and Product Quality

While both personalization and quality improvement both lead to an increase in consumer utility, the two constructs are conceptually quite different. Quality improvement implies enhancing the product / service attributes which all customers unanimously value higher (vertical differentiation - Mussa & Rosen, 1978). On the other hand, personalization implies giving different products to different customers thereby reducing the disutility on the horizontal dimension (Dewan et al 2003). Therefore, the second question we examine is whether personalization and quality are substitutes, i.e., can a firm offer one in lieu of the other? In other words, how do the equilibrium quality levels change when a firm adopts personalization?

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2 [http://www.jupitermedia.com/corporate/releases/03.10.14-newjupresearch.html](http://www.jupitermedia.com/corporate/releases/03.10.14-newjupresearch.html)
1.2 Personalization and Market Structure

Prior literature on product personalization usually considers the case where firms are maximally differentiated on the horizontal dimension (Dewan et al, 2003, Syam & Kumar, 2005). However, in reality, firms may offer similar products and differentiate on quality (Shaked & Sutton, 1982). E.g., consider the competition among online bookstores. Amazon.com and Bestprices.com both sell similar books and are largely undifferentiated on product type. However, Amazon offers a much higher quality in terms of better user interface, online reviews, and additional features such as A9 search capability. It would be interesting to study the impact of market structure on equilibrium profits when firms can adopt personalization. Therefore, the final question we study is: how do equilibrium profits change under different market structures when firms can adopt personalization?

1.3 Literature Review

Previous attempts to model personalization have analyzed product personalization, targeted coupons or promotions, and personalized pricing (Dewan, et al. 2003; Chen, et al. 2001, Choudhary et al 2005). The dominant result in these studies is that the firm which personalizes earns higher profits than the firm which does not personalize. On the other hand, studies have shown that personalization does not lead to higher profits for a firm, even if competitors do not personalize (e.g., Thisse et al 1988, Shafer & Zhang, 1995, Chen & Iyer, 2002). The intuition is that personalization by one firm can lead to intensified price competition in the market such that both firms get lower payoffs in equilibrium. Aron et al (2005) model intelligent agent based personalized pricing in a monopolist setting. Murthy, et al. (2003) summarize the current research in the management science discipline on personalization and provide a survey of the issues involved in personalization. Researchers in computer science and human-computer interaction (Tam, et al. 2003; Smyth, et al. 2000) have conducted controlled experiments and reported that personalization leads to higher response rates from consumers. Dewan et al (2001, 2003) provide a model where a firm serves some customers with customized product and the rest with a standard product. They were one of the first to model the economics of customization of physical goods in a horizontal product differentiation scenario. Their paper introduced...
the idea of a personalizing firm offering a continuum of products on the horizontal dimension rather than a single product. Syam and Kumar (2006) extend this model to more general settings.

All prior models of personalization consider a one-dimensional product differentiation model. The concept of product differentiation - horizontal (Hotelling 1929; d’Aspremont et al 1979) and vertical (Mussa and Rosen 1978; Shaked and Sutton 1982) has been analyzed extensively. However, in most markets, firms must make product positioning decisions on more than one dimension in conjunction with price. While a two-dimensional setting is more complex to analyze, in reality, firms are differentiated both horizontally (taste, physical distance, product attributes etc) and vertically (quality); so a two-dimensional model captures the reality and provides additional insights which would be overlooked in a one dimensional setting. Caplin & Nalebuff (1989) were among the first to prove the existence and uniqueness of equilibrium in a two-dimensional setting for a broad category of distribution functions. Neven and Thisse (1990) solved a two dimensional model for equilibrium price and product differentiation (both horizontal & vertical) and concluded that it is optimal for a firm to differentiate fully only on one dimension i.e., follow a MaxMin strategy. Weber (2001) considers a two dimensional model of competition in the case of information goods and concludes that under perfect information, it is optimal for firms to adopt a Max-Min differentiation strategy. Vandenbosch et al (1995) considers a two-dimensional model where both the dimensions of differentiation are based on quality. They showed that MaxMin is not always the equilibrium in such models, and that under some conditions, firms can find it profitable to differentiate maximally under both dimensions (MaxMax). Degryse (1996) uses a two dimensional model to analyze the adoption of remote access in the banking industry. This model assumes that the horizontal and vertical dimensions are interrelated, whereas in our model, the two dimensions are independent and orthogonal to each other. Further, firms’ quality levels are determined endogenously in our model.

In this research, we extend prior work on personalization in two ways: one, we incorporate a two-dimensional model of product differentiation; and two, we consider personalization in the context of products and services where information is the key element of personalization. Before we present our model, we highlight two key features of a two-dimensional model which are crucial in our analysis:
**Q-F Ratio**: In a two-dimensional model, consumers have a preference for product fit as well as a different willingness to pay for quality. These dimensions are orthogonal to each other and the total consumer utility is the sum of the consumer utility on each dimension. We introduce a term ‘Q-F Ratio’ or ‘Quality-Fit Ratio’ to denote which dimension is more preferred by the consumer. E.g., a low Q-F Ratio indicates that consumers have strong product preferences (e.g., business news vs. political news; high risk investments vs. low risk investments) and would be reluctant to buy something that does not fit their tastes even if the other firm is offering a superior quality. E.g., in the travel industry, consumers are more likely to value product fit (e.g., vacation to Europe vs. African safari) than quality. On the other hand, a high Q-F Ratio indicates that quality levels are more important than product attributes. E.g., in case of credit cards, consumers may care more about quality, as indicated by fraud protection services and level of customer service, than whether the card gives reward points or cash-back. Mathematically, $\gamma = \frac{(Quality \ difference \ between \ firms)}{(Transportation \ cost)}$. If $q_1$ and $q_2$ are the levels of quality offered by firm 1 and firm 2 respectively in the market and $t$ is the transportation cost, then $\gamma = \frac{q_1 - q_2}{t}$.

**Market Structure**: In our model, we consider that the choice of firms’ location is exogenously determined before the start of the game. Prior studies have mainly considered the case where firms are maximally differentiated on the Hotelling line (Dewan et al 2003, Kim, Shi and Srinivasan, 2003). d’Aspremont, et al, 1979 show that firms find it optimal to locate at the opposite ends of the Hotelling line. However, competition between direct marketers can also be represented by firms occupying the same position in the horizontal dimension (e.g. Balasubramanian et al, 1999). We consider both market structures in our model. One, we consider the case where firms are located at the opposite ends of the Hotelling line (Locationally Differentiated, or LD); two, when both firms are situated in the center of the market (Locationally Identical or LI).

Our main results are as follows: one, we show that personalization adoption by a firm may or may not be profitable, even if the competitor does not personalize. Under LD market structure, neither firm finds it profitable to personalize for low values of the Q-F Ratio. However, a firm can find it profitable to
personalize if the effectiveness of the technology is high. Two, for high values of the $Q-F$ Ratio, personalization is profitable for a firm if the competitor does not personalize (under both $LD$ and $LI$). Two, under $LI$ and a low $Q-F$ Ratio, we find that personalization by one firm leads to higher profits for both firms in the market. Three, personalization and quality can be either complements or substitutes. In other words, personalization by a firm can lead it to increase or decrease its equilibrium quality level under different conditions. Four, consumer surplus can increase or decrease with personalization depending on the market structure and the $Q-F$ Ratio. We find that personalization adoption leads to lower (higher) consumer welfare for high (low) $Q-F$ Ratio than no personalization. This contradicts prior literature (Dewan et al 2001) which shows that personalization always leads to increased consumer welfare. Finally, we show in a two dimensional model, given exogenous location choice, firms choose to differentiate on either one ($MaxMin$ differentiation) or both ($MaxMax$) or neither dimension ($MinMin$), depending on the market structure and $Q-F$ Ratio. Low values of $\gamma$ lead to a horizontal dominance ($HD$) equilibrium where firms offer identical quality levels, whereas higher values of $\gamma$ lead to a vertical dominance ($VD$) equilibrium where one firm offers a high quality product and the other firm offers a low quality product.

We extend prior work on personalization in following ways: one, prior work on personalization typically considers a one dimensional model where firms are differentiated on location (Dewan et al 2003) or quality (Choudhary et al 2005). In this research, we consider a two dimensional model where products may be differentiated on both quality and location. Two, we consider the personalization of information goods and services where the marginal cost of personalizing is negligible. Third, as opposed to prior work (Dewan et al, 2003), we consider only product personalization in our model, and not price personalization. This is because most firms which offer information goods in a personalized manner (e.g. wsj.com, emusic.com, movielink.com, vongo.com) charge a standard price for all customers. Also, differential pricing is not always feasible and the practice of price personalization at a mass level has invited negative publicity (e.g. Amazon.com)\(^3\). Finally, we differentiate from prior literature (Dewan et al 2003, Choudhary et al 2005) in

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\(^3\) Personalized pricing is a reasonable assumption for physical goods (Dewan et al 2003) because firms generally charge a higher price for a personalized product than for a standard product (e.g. Lewis Jeans, Lands'End). However, we observe that firms providing
that we use a more general personalization parameter, i.e., we allow for personalization technologies to be imperfect.

The rest of the paper is organized as follows: in section 2, we present our mathematical model. In Section 3, we consider the case where firms are ex-ante locationally differentiated (LD) and solve for equilibrium both with and without personalization. Likewise, we solve for equilibrium when firms are ex-ante locationally identical (LI) in Section 4. In section 5, we calculate the consumer surplus under various equilibriums and in section 6, we discuss the implications of relaxing the assumption of zero marginal cost of quality. Finally, in the last section, we present the discussion and limitations of our research.

2. Model

Before we introduce personalization, we present an outline of a two-dimensional product differentiation model and highlight the equilibrium conditions. We consider a product market which has a broad product variety (horizontal differentiation) and various possible quality levels (vertical differentiation). An example of such a product is credit cards. Different customers have different preferences for various credit card attributes. E.g. co-branded credit cards also offer a huge product variety to customers (e.g. Chase has a variety of co-branded cards such as Chase AAA, Chase AARP, Chase MIT and Harvard and so on). On the other hand, customers also care about the quality of credit cards. Fraud detection services and faster access to live representatives (e.g. the recently introduced Citi Simplicity card) are some examples of how credit card companies are investing in providing a better quality to customers.

To model such a product where consumers value both the ‘product fit’ (choosing a product which closely matches their preferences) as well as ‘product quality’ (higher quality is always preferable to low quality), we consider a two-dimensional model of consumer preferences - a horizontal component \( x \) representing product preference (e.g. Hotelling 1929) and a vertical component \( \theta \) representing willingness to pay per unit of quality (e.g. Shaked and Sutton 1982). Thus the coordinates \((x, \theta)\) represent the position of any consumer in the X-Y plane. We assume:

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personalized information goods charge the same price, whether the customer uses the personalization feature or not (e.g. wsj.com and RealOne SuperPass)

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• **A1:** Consumer preferences are distributed uniformly over a square of unit area on the X-Y plane such that \( x \in [0, 1] \) and \( \theta \in [0, 1] \).

• **A2:** Consumer’s willingness to pay for quality is increasing in quality i.e., \( g(\theta, q) = \theta \cdot q \), where \( \theta \) is consumer type and \( q \) is the quality level. In our model, we assume that the range of quality levels offered in the market always lies between \( [\theta_1, \theta_2] \). In other words, the maximum quality level that a firm can offer is \( \bar{\theta} \) and the minimum quality level that a firm can offer is \( \underline{\theta} \) (\( \overline{\theta}, \underline{\theta} > 0 \)).

• **A3:** Consumer’s disutility due to product misfit, \( m \), is increasing in the distance between the consumer’s preference and the actual product offered by the firm, i.e., \( m(t, x, z) = t \cdot |x - z| \), \( x \) and \( z \) are the location of the consumer and the firm respectively and \( t \) (\( t > 0 \)) is the per unit cost of misfit, also known as the transportation cost. The transportation cost \( t \) captures the range of product variety in the market.

• **A4:** Reservation Price, \( R \) is large enough such that in equilibrium, the entire market is covered. Further we assume that each consumer buys only one unit of the good.

• **A5:** Cost of providing different levels of quality is fixed. This assumption is not critical and we also discuss the implications of relaxing this assumption. As mentioned in prior literature (Vandenbosch, et al 1995), this assumption greatly simplifies the calculations, and as we show in section 6, our results are largely unchanged when we relax this assumption.

Consider two firms in the market competing for customers. They locate themselves at \( z_1 \) and \( z_2 \) and offer products of quality \( q_1 \) and \( q_2 \) at price \( p_1 \) and \( p_2 \) respectively. Thus \( (z_1, q_1) \) and \( (z_2, q_2) \) represent the position of the firms 1 and 2 respectively in the two dimensional space. Without loss of generality, we assume that \( q_1 \geq q_2 \).

Consumer utility for a product for a product \( (z_1, q_1) \) offered by firm 1 is given by \( U_1 = R + \theta \cdot q_1 - t \cdot |x - z_1| - p_1 \). Similarly, for firm 2, \( U_2 = R + \theta \cdot q_2 - t \cdot |x - z_2| - p_2 \). The set of consumers who are indifferent between buying a product from either firm is a line intersecting the X-Y plane. The equation for this line is given by solving \( U_1 = U_2 \). Mathematically,
\[ \theta(x) = \frac{p_2 - p_1}{q_1 - q_2} - \frac{t|x - z_2| - |x - z_1|}{q_1 - q_2}. \] (1)

We analyze a two-stage single period simultaneous move game in a duopoly to find the sub-game perfect equilibrium in prices and quality. In the first stage, both firms choose their qualities and in the second, they choose prices. Location choice is exogenous in our model and we consider two extreme cases based on firms’ location. In one case, we consider that firms are located on the same point on the Hotelling line. In the other case, we consider that firms are located at the opposite ends of the Hotelling line, i.e., firms offer horizontally differentiated products. Such fixed location models are very common in industrial organization literature (Dewan et al 2003, Syam and Kumar 2005). Moreover, location choice represents long term consumer perceptions about a firm (e.g., The Washington Post for political news and The Wall Street Journal for business news) and changing location requires significant investments by firms in product re-positioning.

**Modeling Personalization**

Next, we introduce personalization in our model. We use the framework provided in the Dewan et al (2003) model to operationalize the impact of personalization technology from an economic standpoint. For a standard product offered at a price ‘\(p\)’ at a distance \(x\) from the consumer, the consumer utility for a standard product is given by \(U = R + \theta \cdot q - p - x\), where \(r\) is the reservation price. By definition, personalization is the ability of a firm to be able to offer a product that matches with the users’ tastes and interests. Therefore, personalization can be represented as a firm acquiring the capability of locating at multiple points instead of at a single point on the line representing consumer preferences; therefore the utility that a consumer gets from a personalized product is \(U = R + \theta \cdot q - p\). Contrary to the Dewan et al (2003) model, which assumes that personalization is always perfect, we recognize that there are technological limitations in predicting a consumer’s preference with complete accuracy at all times. We represent this effectiveness by a variable \(\delta\), which indicates the level of personalization. For a given personalization technology, \(\delta\) represents how closely the firm can match the product offering to the consumers’ ideal product. Clearly, \(0 < \delta < 1\) (\(\delta = 0\) represents a non-personalized (or standard) product and \(\delta = 1\) represents an accurately personalized product as given in Dewan et al (2003)). Therefore, we represent the utility function with product personalization as \(U = R + \theta \cdot q\).
Note that disutility changes differently for consumers, depending on their location. In the case of the customization of physical goods (Dewan, et al. 2003), the marginal cost of personalization is positive (and variable) because the product needs to be physically changed for each customer. In the case of digital goods and services, personalization consists of matching the right product with the right consumers (e.g. a website might have thousands of dynamic pages of content or a direct marketer may have hundred of different products). Once the firm incurs basic setup costs, $F$, in terms of hardware and software, the marginal cost of personalization for each additional customer may be negligible (since no new content needs to be created).

3. Locationally Differentiated (LD) Market Structure

In this case firms are located at the two ends such that $z_1 = 0$ and $z_2 = 1$. In this market, customers who are indifferent between buying from either firm (i.e. $U_1=U_2$) lie along the indifference line given by

$$\theta(x) = \frac{p_1 - p_2 - t}{q_1 - q_2} + \frac{2 \cdot t \cdot x}{q_1 - q_2}. \quad (2)$$

The slope of the indifference line depends on the ‘Quality-Fit’ ($Q-F$) Ratio, $\gamma = \frac{q_1 - q_2}{t}$. The $Q-F$ Ratio is a measure of which type of product differentiation is relatively more important to the customer. E.g. A higher $q_1-q_2$ value indicates that firms are strongly differentiated on the vertical dimension; whereas higher the value of $t$, stronger is the effect of horizontal differentiation in the market.

Based on the position of the indifference line on the X-Y plane, the demand for firm 1 and firm 2 can be characterized in various ways, as shown in Figure 1. E.g., if the indifference line intersects both $\theta=0$ and $\theta=1$ lines on the X-Y plane, then each firm captures customers located close to it for all values of $\theta$, as shown in Figure 1a. On the other hand, if the indifference line intersects both the $x=0$ and $x=1$ lines on the X-Y plane, firm 1 captures all customers who have a higher preference for quality and firm 2 captures all customers who have a lower preference for quality, as shown in Figure 1b. Or the indifference line can be somewhere in between, as shown in Figure 1c.
Next, we present a mathematical model to derive the demand for various configurations mentioned above and also highlight conditions under which each type of configuration can occur. Consider an indifference line as shown in Figure 1(a). The indifference line can move up or down parallel to itself by varying the levels of \( p_1 \) (keeping other variables \( q_1, q_2, p_2 \) fixed). E.g., if \( p_1 \) is very low compared to \( p_2 \), firm 1 can capture all the customers in the market. We label this value of \( p_1 \) as \( p_1^1 \), where the indifference line passes through the (1,0) point. On the other hand, if \( p_1 \) is high compared to \( p_2 \), it can capture zero market share. We label this value of \( p_1 \) as \( p_1^4 \), where the indifference line passes through (0,1). The price \( p_1 \) at which the indifference line passes through (1,1) and (0,0) are labeled as \( p_1^2 \) and \( p_1^3 \) respectively. This is shown in Figure 2a and 2b. Therefore, based on the position of the \( \theta(x) \) line, there are three pairs of regions in which \( \theta(x) \) can lie. The calculations involved in finding the demand pair \( D_1, D_2 \) (for firms 1 and 2 respectively) are slightly different in each of the three regions. For a detailed description of firm demand in a two dimensional setting, see Neven et al (1990). Demand in Region II is outlines below. Demand in Regions I and III are obtained similarly and are outlined in Appendix A. The values of \( p_1^1, p_1^2, p_1^3 \) and \( p_1^4 \) in Figure 2a and 2b are calculated by substituting \((x=1, \theta=0)\), \((x=1, \theta=1)\), \((x=0, \theta=0)\) and \((x=0, \theta=1)\) respectively in the indifference line (2).
Mathematically, 

\[
\begin{align*}
p_1^1 &= p_2 - t \\
p_1^2 &= q_2 - q_1 + p_2 - t \\
p_1^3 &= p_2 + t \\
p_1^4 &= q_1 - q_2 + p_2 + t
\end{align*}
\]

Clearly \( p_1^4 \geq p_1^3 \geq p_1^1 \) and \( p_1^4 \geq p_1^2 \geq p_1^1 \)

Two distinct cases arise depending on the value of \( p_1^2 \) and \( p_1^3 \).

i. \( p_1^2 \leq p_1^3 \) (Figure 2a): In this case, the indifference line in Region II intersects both \( \theta=0 \) and \( \theta=1 \) lines on the X-Y plane, as shown in Figure 1a. This implies that each firm captures all customers located close to it, irrespective of their preference for quality. Substituting the values of \( p_1^2 \) and \( p_1^3 \) from (3), \( p_1^2 \leq p_1^3 \) is satisfied if \( t \geq \frac{q_1 - q_2}{2} \), or the Q-F Ratio \( \gamma \leq 2 \). Therefore, this implies that the consumers’ preference for product fit (given by the transportation cost, \( t \)) dominates their preference for quality; therefore, this is known as ‘Horizontal Dominance’ (see Neven et al, 1990). We label this region as \( R^h_{\theta} \). For example, Horizontal Dominance is characteristic of markets where products are highly differentiated and consumers experience a huge disutility if they do not buy a product of their choice (high values of \( t \)).
ii. $p_1^2 \geq p_1^3$ (Figure 2b): In this case, the indifference line in Region II intersects both $x=0$ and $x=1$ lines on the X-Y plane, as shown in Figure 1b. This implies that firm 1 (firm 2) captures all high (low) value customers, irrespective of their horizontal preference. Substituting the values of $p_1^2$ and $p_1^3$ from (3), $p_1^2 \leq p_1^3$ is satisfied if $t \leq \frac{q_1 - q_2}{2}$, or the $Q$-$F$ Ratio $\gamma \geq 2$. Therefore, this implies that the consumers’ preference for quality dominates their preference for variety (given by the transportation cost, $t$); therefore, this is known as ‘Vertical Dominance’ (see Neven et al, 1990). We label this region as $R^v$. For example, Vertical Dominance is characteristic of markets where products are relatively homogenous (low values of $t$) and firms primarily differentiate on quality.

As shown in prior research (Neven et al 1990), the equilibrium in two-dimensional models generally lies in Region II. Therefore, we concentrate our analysis only on Region II. In Appendix A, we test the equilibrium in Region I and Region III, and show that the equilibrium conditions do not hold in these regions.

3.1 Horizontal Dominance

According to the discussion above, horizontal dominance is characteristic of markets with a low $Q$-$F$ Ratio, i.e., quality difference ($q_1$-$q_2$) between firms is low compared to the horizontal disutility parameter $t$. First, we solve for equilibrium under horizontal dominance in two separate cases: one, when no firm offers a personalized product, and two, when one firm offers a personalized product. We consider a two stage game as follows: in the first stage, both firms chose their equilibrium quality levels and in the second stage, both firms choose prices. More details on the two stage game are shown in Appendix A. The results can be summarized as follows:

**Proposition 1a:** When firms are maximally differentiated horizontally and none of the firms personalizes, there exists a pure strategy Nash equilibrium such that the equilibrium prices and profits are given as follows: $q_1 = q_2 = \bar{q}$; $p_1 = p_2 = t$; $\pi_1 = \pi_2 = \gamma$.

This proposition is intuitive because it suggests that if firms are located at end points of a line, they offer the same quality level at the same price. Both firms earn the same profits. Next, we consider the case when
one firm (say firm 1) adopts personalization. Solving the consumer utility functions $U_1 = U_2$, indifference line is now given as $\theta(x) = \frac{p_1 - p_2 - t}{q_1 - q_2} + \frac{t \cdot (2 - \delta) \cdot x}{q_1 - q_2}$. Solving the two stage game for quality and price respectively using backward induction yields the following equilibrium:

**Proposition 1b:** When one firm adopts personalization, the pure strategy in prices and quality is:

\[
p_1 = t \cdot (1 - \frac{\delta}{3}); \quad p_2 = t \cdot (1 - \frac{2 \cdot \delta}{3}); \quad q_1 = q_2 = \theta; \quad \pi_1 = \frac{t \cdot (3 - \delta)^2}{9 \cdot (2 - \delta)^2}; \quad \pi_2 = \frac{t \cdot (3 - 2 \cdot \delta)^2}{9 \cdot (2 - \delta)}.
\]

Both firms earn lower profits and price lower than when none of the firms personalizes.

We can show that $\frac{\partial \pi_i}{\partial \delta} < 0$ for $i=1,2$. This proposition leads to an interesting observation that under LD and HD, personalization leads to lower profits for both firms than the no-personalization case. Further, both firms lower their prices than in the no-personalization case. The intuition is that personalization, in which one firm offers multiple products on the horizontal line, effectively reduces the horizontal differentiation between firms and leads to increased price competition (Tirole, 1988). Ulp and Vulcan, 2000 (henceforth, UV) label this as the ‘competition effect’. But customers who buy from firm 1 also get an increased utility from buying a personalized product, whereby firm 1 can potentially charge a higher price; UV label this as the ‘surplus extraction effect’. Overall the former effect dominates and both firms earn lower profits and price lower than the no-personalization case. These results also hold qualitatively if both firms have the capability to personalize.

### 3.2 Vertical Dominance

Vertical dominance is characteristics of markets with a high $Q$-$F$ Ratio, $\gamma$ i.e., where quality difference ($q_1 - q_2$) between firms is high compared to the horizontal disutility parameter $t$. As in Section 3.1, we set up a two stage game and solve for equilibrium quality and prices. When none of the firms offers a personalized product, the equilibrium is as follows:
**Proposition 2a:** When firms are maximally differentiated horizontally and none of the firms personalizes, for \( \gamma \geq 2 \), there exists a pure strategy Nash equilibrium such that the equilibrium prices and profits are given as follows:

\[
p_1 = \frac{2(\bar{\theta} - \theta)}{3}; \quad p_2 = \frac{\bar{\theta} - \theta}{3}; \quad q_1 = \bar{\theta}; \quad q_2 = \theta; \quad \pi_1 = \frac{4(\bar{\theta} - \theta)}{9}; \quad \pi_2 = \frac{\bar{\theta} - \theta}{9}.
\]

This result is typical of a quality differentiation model where one firm offers a higher quality product at a higher price and the other offers a lower quality product at a lower price. We consider two separates cases: one, when the high quality firm personalizes and two, when the low quality firm personalizes. The result can be summarized in form of the following proposition:

**Proposition 2b:** When the high quality firm adopts personalization and \( \gamma \geq 2 - \delta \), the equilibrium is:

\[
p_1 = \frac{4 \cdot (\bar{\theta} - \theta) + t \cdot \delta}{6}; \quad p_2 = \frac{2 \cdot (\bar{\theta} - \theta) - t \cdot \delta}{6}; \quad q_1 = \bar{\theta}; \quad q_2 = \theta; \quad \pi_1 = \frac{(4 \cdot \bar{\theta} - 4 \cdot \theta + t \cdot \delta)^2}{36(\bar{\theta} - \theta)}; \quad \pi_2 = \frac{(2 \cdot \bar{\theta} - 2 \cdot \theta - t \cdot \delta)^2}{36(\bar{\theta} - \theta)}
\]

On the other hand, when the low quality firm offers personalization and \( \gamma \geq 2 - \delta \), the equilibrium prices and quality levels are:

\[
p_1 = \frac{4 \cdot (\bar{\theta} - \theta) - t \cdot \delta}{6}; \quad p_2 = \frac{2 \cdot (\bar{\theta} - \theta) + t \cdot \delta}{6}; \quad q_1 = \bar{\theta}; \quad q_2 = \theta; \quad \pi_1 = \frac{(4 \cdot \bar{\theta} - 4 \cdot \theta - t \cdot \delta)^2}{36(\bar{\theta} - \theta)}; \quad \pi_2 = \frac{(2 \cdot \bar{\theta} - 2 \cdot \theta + t \cdot \delta)^2}{36(\bar{\theta} - \theta)}
\]

From proposition 2b, it is clear that profits increase for the firm which personalizes and reduce for the firm which does not personalize. Thus both the high quality and low quality firm find it profitable to personalize. The equilibrium quality levels remain unchanged than the no personalization case, but this is driven primarily due to our assumption of zero marginal cost of quality. If both firms have the capacity to adopt personalization, the equilibrium is given as follows:

**Corollary 1:** Under LD and VD, if both firms have the capability to adopt personalization, both firms choose to personalize in equilibrium and the equilibrium profits and prices are the same as the no personalization case in Proposition 2a.

This results suggests that under VD, when firms are symmetric in their capability to adopt personalization, both firms choose to offer a personalized product but the prices and profits remain unchanged than the no personalization case under Nash equilibrium. If we consider a low fixed cost of personalization \((\delta)\), both firms choose to adopt personalization but are worse off than the no-personalization case. This is the classical *Prisoners’ Dilemma* equilibrium.
Finally, the question which arises is whether HD and VD can co-exits for some values of \( \gamma = \frac{q_1 - q_2}{t} \) and whether one is Pareto dominant over the other. We use the results in propositions 1 and 2 above.

**Corollary 2**: In locationally differentiated models, HD dominates VD for \( \gamma < \gamma_i^{**} \), where \( i = H, L \) represent whether the high or low quality firm adopts personalization under VD.

Mathematically,

\[
\gamma_L^{**} = \frac{9 - 2(4 - \delta) \delta + (3 - \delta) \sqrt{9 - \delta(10 - 3 \delta)}}{2(2 - \delta)};
\gamma_H^{**} = \frac{9 - (10 - 3 \delta) \delta + (3 - 2 \delta) \sqrt{9 - 2 \delta(4 - \delta)}}{2(2 - \delta)}
\]

We can show that \( \frac{\partial \gamma_L^{**}}{\partial \delta} < 0; \frac{\partial \gamma_H^{**}}{\partial \delta} < 0 \). This suggests that personalization by either the high quality or the low quality firm leads to a shift in equilibrium from HD to VD, i.e., increase in personalization effectiveness leads to higher quality differentiation between firms in LD models.

### 4. Locationally Identical (LI) Market Structure

In this case, firms are minimally differentiated horizontally and both firms locate at the center of the X-axis. Many firms, which essentially sell undifferentiated goods such as books and CDs, fall in this category where firms try to differentiate by increasing the quality level of user interaction. Online portals such as Yahoo and MSN are another example where firms offer products are horizontally undifferentiated. In the absence of personalization, this is equivalent to a simple vertical differentiation model where one firm offers a higher quality product than the other firm (Moorthy, 1988). We incorporate this market structure in our two dimensional model by considering both firms are located at the center of the market i.e. \( z_1 = z_2 = \frac{1}{2} \). First, we solve for the no-personalization case. Since the firms are located at the same point on the X-axis, customers experience the same disutility if they buy from either firm. In other words, consider a customer located at a distance \( x \) from the center. Her utility is given as \( U_1 = R - \theta q_1 - p_1 - t \cdot x \) and \( U_2 = R - \theta q_2 - p_2 - t \cdot x \). The indifference line is given as \( \theta = \frac{p_1 - p_2}{q_1 - q_2} \). Clearly, the slope of this line is zero and hence the indifference line is horizontal. Only vertical dominance equilibrium is possible in this case. The equilibrium profits and prices can be summarized as:
Proposition 3: If firms are ex-ante similar on the horizontal dimension and no firm personalizes, the equilibrium prices and profits are given as:

\[ p_1 = \frac{2 \cdot (\bar{\theta} - \theta)}{3}; \quad p_2 = \frac{(\bar{\theta} - \theta)}{3}; \quad q_1 = \bar{\theta}; \quad q_2 = \theta; \quad \pi_1 = \frac{4 \cdot (\bar{\theta} - \theta)}{9}; \quad \pi_2 = \frac{\bar{\theta} - \theta}{9} \]

This result follows for the typical vertical differentiation model (Moorthy, 1988). If firms offer undifferentiated products in terms of location, then one firm chooses a higher quality than the other in equilibrium. The high quality firms prices higher and earns more profits than the lower quality firm. No horizontal dominance is possible in the no personalization case because customers experience the same level of disutility from either firm.

4.1 Horizontal Dominance

Personalization introduces a measure of horizontal differentiation in our model. Consumers experience lower locational disutility if they buy a personalized product than if they buy a standard product. E.g., if firm 1 personalizes, the consumer utility now becomes

\[ U_1 = R - \theta q_1 - p_1 \cdot t \cdot x(1-\delta) \]

and

\[ U_2 = R - \theta q_2 - p_2 \cdot t \cdot x; \]

the indifference line

\[ \theta(x) = \frac{p_1 - p_2 - t \cdot \delta \cdot x}{q_1 - q_2} \]

clearly depends on \( x \) and hence locational differentiation is created. First, we consider the case of horizontal dominance.

In case one firm offers a personalized product, the indifference line is given as:

\[ \theta(x) = \frac{p_1 - p_2 - t \cdot \delta \cdot x}{q_1 - q_2} \]

where \( x \) is the distance between the customer’s ideal product and the center of the market \((z= \frac{1}{2})\). Solving for two-stage sub-game perfect equilibrium in quality and prices, we get the following results:

Proposition 4: In a vertically differentiated market and \( \gamma < \frac{\delta}{2} \), when firm 1 personalizes, the equilibrium prices and quality are given as follows:

\[ p_1 = \frac{2 \cdot t \cdot \delta}{3}; \quad p_2 = \frac{t \cdot \delta}{3}; \quad q_1 = \bar{\theta}; \quad q_2 = \theta; \quad \pi_1 = \frac{4 \cdot t \cdot \delta}{9}; \quad \pi_2 = \frac{t \cdot \delta}{9} \]

These results are interesting because they suggest that even though firms are locationally identical, HD can still be the equilibrium. In such an equilibrium, the firm which personalizes captures customers located
away from the center of the market and the firm which does not personalize captures customers located close to the center; and both firms offer a high quality level. This is the case of MinMin differentiation, i.e., both firms are minimally differentiated in terms of both location and quality. It is not surprising that the profits in this case depend on the personalization parameter, $\delta$. If $\delta=0$ (no-personalization case), this reduces to the classical Bertrand equilibrium where both firms earn zero profits. Therefore personalization adoption enables undifferentiated firms to earn non-zero profits. This result is also interesting because it suggests that personalization adoption by one firm leads to an increase in profits for both firms, i.e., $\frac{\partial \pi_i}{\partial \delta} > 0$ where $i=1,2$.

The firm which personalizes earns a higher profit than the firm which does not personalize. The intuition for this result is that the effect of personalization is to create horizontal differentiation in a market where firms are ex-ante similar. Customers located farther away from the firms get a higher increase in utility due to personalization than customers located closer to the firms. This enables firms to price higher and extract a higher surplus.

**4.2 Vertical Dominance**

As in the earlier section, we examine personalization under vertical dominance in two separate cases: one, when the high quality firm personalizes and two, when the low quality firm personalizes. The results can be summarized in the following proposition:

**Proposition 5:** When the high quality firm personalizes and $\gamma > \frac{\delta}{2}$, the equilibrium prices and quality levels are given as:

$$p_1 = \frac{8\bar{\theta} - 8 - \theta + t \cdot \delta}{12}; \quad p_2 = \frac{4\bar{\theta} - 4 \cdot \theta - t \cdot \delta}{12}; \quad q_1 = \bar{q}; \quad q_2 = \theta; \quad \pi_1 = \frac{(8\bar{\theta} - 8 - \theta + t \cdot \delta)^2}{144(\bar{\theta} - \theta)}; \quad \pi_2 = \frac{(4\bar{\theta} - 4 \cdot \theta - t \cdot \delta)^2}{144(\bar{\theta} - \theta)}$$

When the low quality firm personalizes and $\gamma > \frac{\delta}{2}$, the equilibrium prices and quality levels are given as:

$$p_1 = \frac{8\bar{\theta} - 8 - \theta - t \cdot \delta}{12}; \quad p_2 = \frac{4\bar{\theta} - 4 \cdot \theta + t \cdot \delta}{12}; \quad q_1 = \bar{q}; \quad q_2 = \theta; \quad \pi_1 = \frac{(8\bar{\theta} - 8 - \theta - t \cdot \delta)^2}{144(\bar{\theta} - \theta)}; \quad \pi_2 = \frac{(4\bar{\theta} - 4 \cdot \theta + t \cdot \delta)^2}{144(\bar{\theta} - \theta)}$$
This result is similar to the LD case in section 3 where the firm which personalizes earns a higher profit than the no personalization case. Also, similar to Corollary 2, we highlight conditions under which either HD or VD Pareto dominates the other in LI models. The results can be summarized as:

**Corollary 2:** In locationally identical models, HD dominates VD for \( \gamma < \gamma_i^{**} \), where \( i = H, L \) represent whether the high or low quality firm adopts personalization under VD.

Mathematically, \( \gamma_H^{**} = \left(3 \delta + 2\sqrt{2} \delta \right)/4 \) and \( \gamma_L^{**} = \delta/2 \). We can show that \( \frac{\partial \gamma_H^{**}}{\partial \delta} > 0; \frac{\partial \gamma_L^{**}}{\partial \delta} > 0 \). This suggests that personalization by either the high quality or the low quality firm leads to a shift in equilibrium from VD to HD, i.e., increase in personalization effectiveness in effect leads to lower quality differentiation between firms in LI models.

5. Consumer Surplus

Finally, it would be interesting to study the effect of personalization on consumer welfare. Opponents of personalization technologies argue that a firm which gathers information about consumers and offers personalized products can extract maximum consumer surplus by charging high prices. On the other hand, proponents of personalization argue that personalized products offer higher utility to the consumer and the benefits of personalization far outweigh the costs imposed on consumers due to high prices. In this section, we calculate the change in consumer surplus when one firm in the market offers personalized products.

In our analysis of a two dimensional market, consumer surplus is obtained by talking a representative consumer at any point \((x, \theta)\) in the X-Y plane. In an LD market where firm 1 offers a personalized product and firm 2 offers a standard product, the surplus of a consumer who buys from firm 1 is

\[
U_1 = R + \theta \cdot q_1 - p_1 - x(1 - \delta)
\]

and that of a consumer who buys from firm 2 is

\[
U_2 = R + \theta \cdot q_2 - p_2 - (1 - x)
\]

The total consumer surplus is calculated by integrating the consumer surplus over the respective region of demand. An outline of calculations involved in calculating the consumer surplus is shown in Appendix A.

**Proposition 6a:** Under LD, if one firm has the capability to personalize, overall consumer surplus can either increase or decrease or remain the same depending on the Q-F ratio \( \gamma \).
• For low values of $\gamma(<\gamma^1)$, neither of the firms finds it optimal to adopt personalization, therefore, CS remains the same as no-personalization.

• For intermediate values of $\gamma(\gamma^1<\gamma<\gamma^3)$, no-personalization weakly dominates personalization in terms of CS.

• Finally for high values of $\gamma(\gamma>\gamma^3)$, consumer surplus is always greater under personalization than under no-personalization. Also, CS is the highest when the high quality firm personalizes.

Mathematically, $\gamma^1 = \gamma_H^{**}$ and $\gamma^3 = \gamma_L^{**}$ are the values of $\gamma$ as given in Corollary 2 and $\gamma^3 = 4.5$ Figure 3a plots the consumer surplus for the $LD$ market structure when either firm can adopt personalization as well as for the no-personalization case (for $q_2=1, t=1, \delta=1$).

This intuition for this proposition is as follows: consumer surplus is always greater under $HD$ than under $VD$ because differentiating on the vertical dimension relaxes price competition between firms and increases profits at the expense of consumer welfare. Therefore, for low values of $\gamma$, when $HD$ is the dominant equilibrium, consumer surplus is higher. For high values of $\gamma$ $VD$ is the dominant equilibrium and consumer surplus decreases. Personalization leads to a higher consumer surplus than the no–personalization case under $VD$. Proposition 6a is interesting because it suggests that consumers are not always better off in presence of
personalization. This contradicts prior literature based on one-dimensional models (Dewan et al 2001) that personalization always leads to higher consumer surplus.

Next, we calculate the consumer surplus under the LI market structure and summarize the results in the following proposition.

**Proposition 6b:** When both firms are located at the center of the Hotelling line and one firm has the capability to personalize, the consumer surplus in equilibrium is given as follows:

- For low values of \( \gamma (\gamma^b < \gamma^a) \), the consumer surplus is greater in the no-personalization case than when either firm adopts personalization.
- For intermediate values of \( \gamma (\gamma^b < \gamma < \gamma^a) \), consumer surplus under personalization is always higher than the no-personalization case if the low quality firm adopts personalization.
- For \( \gamma > \gamma^b \), the consumer surplus is always higher when either firm adopts personalization. Further consumer surplus is higher when the high quality firm adopts personalization than when the low quality firm adopts personalization.

Mathematically, \( \gamma^a = \gamma_h^* \) and \( \gamma^b = \gamma_l^* \) are the values of \( \gamma^* \) as given in Corollary 3. The intuition is the same as for Proposition 6b. Figure 3b shows the consumer surplus under LI market structure (for \( q_2 = 1, t = 1, \delta = 1 \)).

![Figure 3b Consumer Surplus in an LI model](image-url)
6. Non-zero Cost of Quality and Sensitivity Analysis

In this section, we discuss the implication of relaxing the assumption of zero marginal cost of quality and show that under most conditions, our results still hold. We assume a general convex cost function $c(q)$ such that $c'(q)>0$ and $c''(q)>0$. Therefore, if firm 1 and firm 2 offer products of quality $q_1$ and $q_2$ respectively, the new profit function is given as: $\pi_1^{\text{new}} = \pi_1 - c(q_1); \pi_2^{\text{new}} = \pi_2 - c(q_2)$, where $\pi_1$ and $\pi_2$ are the profit functions when cost of quality is zero. Further, we normalize the cost function such that $c(\theta) = 0$. Zero (or linear) marginal costs of quality restricts the equilibrium quality levels to end-point solutions. By assuming a convex marginal cost to quality, we can also perform a sensitivity analysis to examine how equilibrium quality levels change due to personalization adoption. We examine the cases one by one:

**Vertical Dominance**: Under vertical dominance, both in case of LD and LI, $\frac{\partial \pi_1}{\partial q_1} > 0$ for all values of $q_2$ and $\frac{\partial \pi_2}{\partial q_2} < 0$ for all values of $q_1$, where firm 1 and firm 2 are the high quality and low quality firm respectively ($q_1 \geq q_2$). Therefore, for non-zero marginal cost of quality, firm 2 still chooses the lowest level of quality, i.e., $\theta$. On the other hand, $\pi_1$ is convex and monotonically increasing in $q_1$. Therefore, depending on the convexity of the cost function, firm 1 chooses an equilibrium quality level $q_1^{\text{new}}$ such that $q_1^{\text{new}} \in [\theta, \theta]$. How does the overall equilibrium change in this case? One, the vertical differentiation in the market decreases (since $q_1 < \theta$). These results also hold when either the low or the high quality firm personalizes, because the comparative statistics still $\frac{\partial \pi_1}{\partial q_1} > 0$ and $\frac{\partial \pi_2}{\partial q_2} < 0$ hold for all permissible values of $q_1, q_2$ and $\delta$.

Next, we do a sensitivity analysis of equilibrium quality level with respect to the personalization parameter $\delta$ and summarize the overall results in terms of the following proposition:

**Proposition 7a**: Under VD (both under LD and LI), increase in personalization effectiveness leads to a decrease in the equilibrium quality level offered by the firm, i.e., $\frac{\partial q_1}{\partial \delta} < 0; \frac{\partial q_2}{\partial \delta} = 0$. 

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Proof of this proposition is shown in Appendix A. This shows that under VD, personalization and quality are substitutes when the high quality firm adopts personalization, i.e., if the high quality firm adopts personalization, it can offer a lower equilibrium level of quality. Infact, the high quality firm offers a lower quality level irrespective of which firm adopts personalization. We can also verify that the profits are qualitatively similar as in the case of zero marginal cost of quality. In other words, for non-zero marginal cost of quality, the firm which personalizes (does not personalize) earns higher (lower) profit than the no-personalization case.

**Horizontal Dominance:** Under horizontal dominance, both in case of LD and LI, \( \frac{\partial \pi_i}{\partial q_i} > 0 \) for \( i = 1, 2 \) and for all values of \( q_1, q_2 \) and \( \delta \). Therefore, under zero marginal cost of quality, both firms choose the highest permissible levels of quality \( \bar{\theta} \). Hence under positive marginal costs of quality, firms offer quality levels \( q_1 \) and \( q_2 \) such that \( q_1, q_2 \in [\bar{\theta}, \theta] \), depending on the convexity of the cost function. Moreover, the firm which personalizes earns a higher profit than the competitor. Suppose firm 1 offers a personalized product. Since both \( \pi_1 \) and \( \pi_2 \) are convex and monotonically increasing in \( q_1 \) and \( q_2 \) respectively and \( \pi_1' > \pi_2' \), firm 1 offers at least a higher quality product than firm 2. This is shown in Figure 4.

![Figure 4: Graphical Representation of Equilibrium Quality Levels under HD](image-url)
Therefore, relaxing the zero marginal cost of quality assumption leads to vertical differentiation in a model of horizontal dominance. The overall result can be summarized in form of the following proposition.

**Proposition 7b:** Under HD and LD, increase in personalization effectiveness leads to an increase in the equilibrium quality level offered by the firm which personalizes, i.e., $\frac{\partial q_1}{\partial \delta} > 0$. In other words, under HD, personalization and quality are complements. Further, personalization leads to an increase in quality differentiation in equilibrium, i.e., $\frac{\partial (q_1 - q_2)}{\partial \delta} > 0$.

On the other hand, under HD and LI, firm which offers a personalized product lowers its quality level as the effectives of personalization increases, i.e., $\frac{\partial q_1}{\partial \delta} < 0$, i.e., personalization and quality are substitutes.

Personalization also leads to a decrease in vertical differentiation in the market, i.e., $\frac{\partial (q_1 - q_2)}{\partial \delta} < 0$.

Next, we estimate the impact of personalization on firm profits in case of HD. Under LI, we can show that $\frac{\partial \pi_1}{\partial \delta} > 0; \frac{\partial \pi_2}{\partial \delta} > 0$, i.e., the earlier results that personalization by one firm leads to increase in profits for both firms still holds after considering positive and convex marginal costs of quality. However, under LD, the results change slightly under positive and convex marginal costs of quality. The next corollary summarizes the equilibrium under LD and HD:

**Corollary 4:** The firm which does not personalize earns lower profits, i.e., $\frac{\partial \pi_2}{\partial \delta} < 0$. The firm which personalizes can earn higher or lower profits than the no personalization case depending on the effectiveness of personalization. In other words, $\frac{\partial \pi_1}{\partial \delta} > 0$ for $\delta$ greater than a certain threshold value, $\delta^*$. The threshold value, $\delta^*$ depends on the convexity of the cost function. Proof of this corollary is shown in Appendix A. This result is interesting because it suggests that if the effectiveness of personalization is high enough, a firm can find it profitable to personalize in a locationally differentiated market when the Q-F Ratio is low. This result is unique to a two-dimensional model because one dimensional models, which do not
consider quality differentiation, can overlook the fact that a firm can personalize as well as offer a higher quality level to make more profits than the no-personalization case.

We highlight the results by considering a specific functional form. We use a quadratic cost function \( c(q) = c \cdot q^2 \). We solve the two stage game using backward induction as in Section 3.1. The profit functions are given as \( \pi_1 = D_1 \cdot p_1 - c \cdot q_1^2 \); \( \pi_2 = D_2 \cdot p_2 - c \cdot q_2^2 \). The results are given in the following proposition:

**Proposition 7c:** Under the condition that \( c > \frac{1}{36t} \), when one firm personalizes, the equilibrium prices and quality are given as follows:

\[
\begin{align*}
    p_1 &= \frac{t (2 - \delta) (12 ct (3 - \delta) - 1)}{36 ct (2 - \delta) - 2}; \\
    p_2 &= \frac{t (2 - \delta) (12 ct (3 + 2 \delta) - 1)}{36 ct (2 - \delta) - 2}; \\
    q_1 &= \frac{12 ct (3 - \delta) - 1}{12 c (18 ct (2 - \delta) - 1)}; \\
    q_2 &= \frac{12 ct (3 - 2 \delta) - 1}{12 c (18 ct (2 - \delta) - 1)}.
\end{align*}
\]

Profits of firm which personalizes are decreasing in \( \delta \) for low values of \( \delta (\delta < \delta^*) \) and increasing in \( \delta \) for high values of \( \delta (\delta > \delta^*) \).

Mathematically, \( \delta^* = \frac{3 (36 ct - 1) - \sqrt{36 ct - 1)(36 ct + 7)}}{72 ct} \). This proposition is interesting because it suggests that for non-zero cost of quality, personalization is actually profitable for a firm even under LD market structure. This is interesting because similar models in a one dimensional setting suggest that personalization leads to increased price competition in the market (Ulp and Vulcan 2000). The intuition is as follows: we can verify that \( \frac{\partial q_1}{\partial \delta} > 0; \frac{\partial q_2}{\partial \delta} < 0 \). In other words, personalization leads to an increase in quality differential between the firms, which results in higher profits for firm 1. The firm which personalizes lowers its price and increases it quality while the firm which does not personalize lowers both its price as well as its quality. For high values of \( \delta \) the increased profit due to quality differentiation dominates the price competition effect due to personalization. Therefore for high values of \( \delta \), firm 1 can find it profitable to personalize. The results of this section can be summarized in form of the following table.
### Table

<table>
<thead>
<tr>
<th>Market Structure</th>
<th>Equilibrium</th>
<th>Personalize</th>
<th>Profits</th>
<th>Quality</th>
</tr>
</thead>
<tbody>
<tr>
<td>LD ((x_1 = 0; x_2 = 1))</td>
<td>HD</td>
<td>Firm 1</td>
<td>(\frac{\partial \pi_1}{\partial \delta} &gt; 0) for (\delta &gt; \delta^<em>) (\frac{\partial \pi_1}{\partial \delta} &lt; 0) for (\delta &lt; \delta^</em>) (\frac{\partial \pi_2}{\partial \delta} &lt; 0)</td>
<td>(\frac{\partial q_1}{\partial \delta} &gt; 0); (\frac{\partial q_2}{\partial \delta} &lt; 0)</td>
</tr>
<tr>
<td>VD</td>
<td>Firm 1</td>
<td>(\frac{\partial \pi_1}{\partial \delta} &gt; 0); (\frac{\partial \pi_2}{\partial \delta} &lt; 0)</td>
<td>(\frac{\partial q_1}{\partial \delta} &lt; 0); (\frac{\partial q_2}{\partial \delta} = 0)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Firm 2</td>
<td>(\frac{\partial \pi_1}{\partial \delta} &lt; 0); (\frac{\partial \pi_2}{\partial \delta} &gt; 0)</td>
<td>(\frac{\partial q_1}{\partial \delta} &lt; 0); (\frac{\partial q_2}{\partial \delta} = 0)</td>
<td></td>
</tr>
<tr>
<td>LI ((x_1 = x_2 = 1/2))</td>
<td>HD</td>
<td>Firm 1</td>
<td>(\frac{\partial \pi_1}{\partial \delta} &gt; 0); (\frac{\partial \pi_2}{\partial \delta} &gt; 0)</td>
<td>(\frac{\partial q_1}{\partial \delta} &lt; 0); (\frac{\partial q_2}{\partial \delta} &gt; 0)</td>
</tr>
<tr>
<td>VD</td>
<td>Firm 1</td>
<td>(\frac{\partial \pi_1}{\partial \delta} &gt; 0); (\frac{\partial \pi_2}{\partial \delta} &lt; 0)</td>
<td>(\frac{\partial q_1}{\partial \delta} &lt; 0); (\frac{\partial q_2}{\partial \delta} = 0)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Firm 2</td>
<td>(\frac{\partial \pi_1}{\partial \delta} &lt; 0); (\frac{\partial \pi_2}{\partial \delta} &gt; 0)</td>
<td>(\frac{\partial q_1}{\partial \delta} &lt; 0); (\frac{\partial q_2}{\partial \delta} = 0)</td>
<td></td>
</tr>
</tbody>
</table>

### 6. Conclusions and Discussion

In this research, we extend prior work on personalization in several ways: one, we consider a more general model where firms make decisions about price and quality at the same time; two, we model personalization in the context of products and services where information is the key element of personalization; finally we model equilibrium conditions under different market structures. We find that such a two-dimensional setting gives us more insights than one-dimensional models. E.g., a one-dimensional model predicts that personalization by a firm in a duopoly always leads to lower profits when firms locate at end points of a Hotelling line, even if the competitor does not personalize (Tirole et al 1988). For a two-dimensional model, we introduce the term Quality-Fit \((Q-F)\) Ratio to measure whether consumers value the right product fit or a better quality product more. We show when firms are locationally differentiated (i.e., are located at opposite ends of the Hotelling line), prior results hold only when the \(Q-F\) ratio is low and when the effectiveness of the personalization technology is low. When the \(Q-F\) Ratio is high, personalization leads to higher profits in such a model. Further, the firm which personalizes earns a higher profit and charges a higher price than the firm which does not personalize. For low \(Q-F\) Ratio, a firm which personalizes can still...
earn higher profits than the no-personalization case, provided the effectiveness of the technology is high. E.g., our model predicts that in case of competition between differentiated products (such as emusic.com versus countrymusic.com or wsj.com versus washingtonpost.com), personalization is adopted by a firm if consumers have a strong preference of product quality over product fit or if the effectiveness of the technology is high.

We also consider the case when firms are locationally identical on the horizontal axis. We find that for low $Q-F$ ratio, profits of both firms increase with personalization. E.g., consider the competition between Amazon.com and Bestprices.com in the online book stores market where the products are largely undifferentiated and the preference for product fit is high (e.g., a customers who is interested in one type of books (say, computer books) cannot be easily persuaded to buy another type of books (e.g., business books). Our model predicts that in such a scenario, personalization by the high quality firm (in this case, Amazon.com) will result in higher profits for both firms. The intuition is that personalization relaxes the Bertrand competition between firms and both firms price higher and earn higher profits in presence of personalization. This result is also unique to a two-dimensional model because it suggests that personalization by one firm can lead to increase in profits for both firms. Finally, we find that consumer surplus can either increase or decrease when one firm adopts personalization depending on the market structure and the $Q-F$ Ratio.

This research also contributes to the literature on two dimensional differentiation models. We show that $MaxMin$ equilibrium is not always dominant in such model (Neven et al 1991). Given that location choice is exogenously determined, we show that firms may choose to differentiate on both ($MaxMax$) or one ($MaxMin$) or none ($MinMin$) dimensions depending on the market structure, personalization adoption and the $Q-F$ Ratio. The $MinMin$ equilibrium is especially interesting because it suggests that under some conditions, personalization allows firms choose minimum differentiation on both dimensions. E.g, personalization can enable firms such as Mp3.com and E-music, or dealcatcher.com and deals2buy.com to differentiate and make positive profits even though both offer similar services.
Although a two two-dimensional model captures reality more closely than a pure horizontal differentiation only or pure vertical differentiation only, firms use a variety of strategic tools which can be too complex to capture in a single model. E.g., our model considers symmetric personalization capabilities for both firms. Future research can capture the case when firms are asymmetric in their personalization capabilities (firms have different values for $\delta$). Also, pricing of information goods can be complex in reality. E.g., some firms charge a per product price while others charge a subscription fee or a mix of both. Some firms give away their products for free in exchange for advertising revenues. Future research can attempt to capture the impact of personalization in each of these scenarios.
Essay 2: Personalization, Information Sharing and Privacy – An Analytical Perspective

“If I have a million customers, I should have a million different web stores.”

Jeff Bezos, Chief Executive Officer of Amazon.com

1. Introduction & Literature Review

1.1 Personalization

Personalization is defined as the process of identifying the exact product requirements of each individual customer and personalizing the standard product to fit her preferences. Personalization is especially suited in online environments where vendors can personalize not only products, but also other aspects of the shopping experience such as advertisements, product recommendations and customer service interactions. The driving force behind personalization of digital goods on the internet is the information overload created by the proliferation of numerous websites, as well as the increase in links and sub-links within each website. For example, iExplore is a travel portal which features more than 50,000 pages of dynamic content, including 1,056 separate trips for hiking, trekking, and walking. It uses ATG Dynamo personalization technology to deliver content to site visitors based on their particular interests, helping customers find the content they want with far fewer clicks and in less time.

Two types of consumer information are useful for firms to offer a personalized product – personal information such as name, demographics and email id; and product preference information such as past purchases and browsing behavior. Consider a firm sending credit card offers to potential customers. Credit card offers have many attributes such as annual fees, membership points and APR; and different customers may value these attributes differently. E.g. some customer might value a low APR more than a low annual fee. A ‘mass marketer’ will mail the same offer to all the customers; on the other hand, a ‘targeted marketer’ offers a personalized credit card to each individual customer. Another example is that of a financial firm selling investment opportunities to its customers. For simplicity, we assume that customers have two types of preferences for risk – low and high. A firm which has access to consumer information can offer different investment opportunities to consumers based on their risk profile. Other examples of digital goods where consumer differ in their preference for product attributes include online news (e.g. business vs. general news) and television guides (e.g. reality TV vs. educational programs). Even firms which sell non-customizable
physical goods (e.g. books, apparel) can create a personalized experience for their customers by tailoring the non-product attributes (e.g. Amazon.com uses personalized recommendation and one-click checkout; Landsend.com allows customers to create a personalized virtual model where they can try the clothes online before buying). Personalized catalogs are another example where firms can sell undifferentiated products in a personalized way.

A common feature of these examples is that personalization consists of reducing the information overload. Too much information creates a disutility for consumers who have to spend time and effort in locating the right product or information. Personalization therefore consists of matching the right information with the right consumer. In such a setting, the marginal cost of personalization is negligible because no new content needs to be created. This is different than the personalization of physical goods, such as vitamins or Levi’s Jeans, where the physical product needs to be changed for different customer and can lead to increased costs due to the reduction in economies of scale (Dewan et al, 2003).

1.2 Information Sharing, Ownership and Privacy

Consumer information is central to a firm’s ability to offer a personalized product. Therefore, we would expect that firms which possess consumer information have an advantage over firms which do not possess any consumer information and that firms would always prevent sharing this information with other firms. However nothing can be farther than truth. The sale or exchange of consumer information is widespread in practice. Customer lists are sold or rented without the knowledge or consent of the customers (Culnan 1995). As Chen et al (2001) point out “more than 600 catalog marketers routinely exchange the purchase information of individual customers with their competitors. This practice of exchanging proprietary customer information baffles industry analysts”. In e-commerce too, firms routinely exchange consumer information with other firms. Just 42% of companies have a policy of not sharing information with anyone without express permission.⁴ E.g. the privacy policy of many websites includes a clause such as “we may share our mailing list (your name and physical address) and your general shopping activity information with a few select companies whose products and services are similar to ours.” The development of open standards (e.g.

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⁴ [http://www2.cio.com/analyst/report3857.html](http://www2.cio.com/analyst/report3857.html) - dated 07/11/06
IBM’s EPAL - Enterprise Privacy Authorization Language) and industry consortia (e.g. Consumer Profile Exchange - CPExchange) further facilitates the sharing of consumer information both across and within businesses in a privacy enabled manner. Network advertisers (DoubleClick.com, Revenue Science & Real Networks) and online shopping malls (shopping.com & pointshop.com) track consumers visiting different online vendors and pool this information to obtain an overall online profile of consumers. This is an indirect information sharing mechanism because information collected at one website (e.g. Yahoo) through a third party can be used to offer personalized content or banner advertisement at a different website (e.g. Msn). Co-operative databases are another example where direct marketers share information with each other. Members of a co-operative database upload information about their consumers (personal and preference information) to a central database owned and operated by a third party; members can also download consumer profiles contributed by other members and send targeted advertisements to these customers. E.g. Roman Alliance Database was founded in 2004 and has a membership of more than 380 businesses and a customer list of 50 million customers. Other co-operative marketers include Abacus B2B Alliance, Direct Media’s Data Warehouse and Meritdirect’s Database (Catalog Age, May 2004, Pg 47). Chen, et al. (2001) mention that a firm can share information in any of the following three ways: (1) by exchanging consumer information; (2) by selling consumer information to competitors; and (3) by giving away consumer information for free to competitors. E.g. Wachovia transferred consumer information to MBNA so that the latter could target these consumers with credit card offers.

The concept of information sharing has been extensively studied in areas such as supply chain management and information security (Lee et al, 2000, Gal-Or and Ghose, 2004). Lee et al, (2000) model the case when partners in a supply chain share demand information. Gal-Or (1985) considers the equilibrium when firms share demand information with competing firms. But sharing of consumer information between firms for the purpose of product personalization has not been analyzed in detail so far. Our work follows closely from Chen et al 2001 who consider the economics of sharing consumer information between firms in the context of targeted advertising. Our research differs from Chen at al (2001) in the following ways: one, we endogenize the scope of personalization in our model; two, while Chen et al (2001) consider...
homogenous product, we assume that the products are horizontally differentiated and personalization reduces the consumers’ disutility from a standard product; three, we allow for selective information sharing, i.e. a firm strategically shares information about only a fraction of customers rather than all the information; finally, our research is also one of the first to model different ownership structures and derive conditions under which consumers allow firms to share their information with other firms.

Personalization and information sharing create the need for protecting consumers’ privacy. In a survey by Forrester Research, 90% of online users want the right to control how their personal information is used after it is collected. Some consumers are also privacy conscious and may take steps to avoid being tracked by the firm for personalization. E.g. consumers can delete cookies or use an anonymous payment system to avoid establishing a purchase history (Acquisiti and Varian, 2005). As shown in empirical literature on privacy, consumers do not like firms to use their information for a different purpose than what was originally stated at the time of information collection (Culnan 1993). Prior literature on direct marketing and privacy shows consumers are concerned about what firms know about them, how they obtain this information and how they use this information.\footnote{See Nowak and Phelps (1995) for a brief survey of this literature.} Westin (1967) defines privacy as a consumer’s ability to control the terms under which personal information is collected and used. Consumers are likely to be wary of personalization due to the possibility of privacy violation (Cranor 2003).

With this motivation, we propose the following research questions: One, what is the optimal scope of personalization when consumers differ in their preference for product attributes? Two, under what conditions do firms have an incentive to share consumer information with their competitors? Three, what is the impact of information sharing on consumer welfare? Four, how does the equilibrium change when information ownership lies with individual consumers and not with firms?

We answer the above questions using a simple duopoly model of horizontal product differentiation under the assumption that one firm has exogenously acquired the ability to offer a personalized product for a fraction of customers in order to study the firm’s incentive to share such information. We also assume that the rest of the customers are privacy conscious and do not wish to share their information in exchange for a
personalized product. Our main results are: one, a firm chooses to offer a personalized product to select customers in a market rather than to all the customers even if the marginal cost of personalizing for an additional customer is zero. Two, under some conditions, a firm prefers to share consumer information with its competitor leading to an increase in profits for both firms. This information sharing can lead to a higher surplus for consumers and also to a redistribution of surplus from consumers who receive a standard product to consumers who receive a personalized product. Third, firms are better off when a fraction of consumers in the market is privacy sensitive and always prefers to receive a standard product. Finally, under some conditions, information sharing is viable even if individual consumers have information ownership and decide whether to allow firms to share their information. Overall, consumer welfare increases or remains the same when consumers have information ownership and can prevent a firm from sharing the same with the other firm.

1.3 Literature Review

We model personalization as a special case of product proliferation in which consumers are heterogeneous in their product preference and the firm can provide each consumer her desired product (Dewan et al, 2003). If firms are maximally differentiated ex-ante on the Hotelling line (Hotelling, 1929) and one firm offers each customer her desired product, this effectively lowers the horizontal differentiation between firms. As pointed out by Tirole (1988, Pg. 287), reduction in horizontal differentiation leads to lower profits for both firms. Ulp and Vulcan, 2000 show similar results when firms offer personalized prices. Dewan et al 2003 show that in an asymmetric duopoly (where only one firm has the capability to personalize) personalization leads to increased profits for the firm which offers a personalized product. However their results are, in part, driven by the assumption that the firm which personalizes also has the ability to use first degree price discrimination. It is not clear if their results would hold if this assumption is relaxed.6 Differential pricing is not always feasible and the practice of price personalization at a mass level has invited negative publicity (e.g. Amazon.com).

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6 Personalized pricing is a reasonable assumption for physical goods (Dewan et al 2003) because firms generally charge a higher price for a personalized product than for a standard product (e.g. Lewis Jeans, Lands’End). However, we observe that firms providing
Other studies have analyzed the economics of personalization using different contexts such as targeted coupons or promotion and personalized pricing (Shaffer and Zhang, 1995; Chen et al, 2001; Thisse et al, 1988). The dominant result of these studies is that when firms in a duopoly market are symmetric in their capability to personalize, both firms will choose to personalize but end up making lower profits than when none of the firms personalizes (known as the Prisoner’s Dilemma). Shaffer and Zhang (2002) extend this analysis to show that when firms are asymmetric in their personalization capabilities, the firm which has a better capability to personalize earns higher profits. Aron et al (2005) model intelligent agent based personalized pricing in a monopolist setting. Murthy, et al. (2003) summarize the current research in the management science discipline on personalization and provide a survey of research issues in personalization.

Researchers in computer science and human-computer interaction (Tam, et al. 2003; Smyth, et al. 2000) have conducted controlled experiments and reported that personalization leads to higher response rates from consumers. When a firm has the capability to offer a different product to customers who have different tastes, an important question that arises is whether the firm should personalize for all customers in the market or should it restrict the scope of personalization by offering a personalized product to select customers. Schmalensee (1978) shows that firms can restrict entry by offering a broad product scope. Klemperer (1987) showed that in markets with switching costs, over-investing in the pre-entry customer base confers a strategic advantage on the incumbent. Telang and Rajan (2002) suggest that in a market with switching costs, firms are sometimes better off restricting their user base. Murthy et al (2003) and Laudon (1996) highlight the importance of examining different information ownership structures related to consumer information.

The rest of this paper proceeds as follows: In section 2, we present our model and summarize the preliminary results. In section 3, we consider the impact of information sharing on consumer surplus. In section 4, we model the case when consumers have ownership to the information that they share with firms. Finally in section 5, we highlight the conclusions and scope for future research.
2. Model

Our model is set up as follows: We assume that consumers are uniformly distributed along a unit line (Hotelling, 1929) and that firms are maximally horizontally differentiated. In a traditional model of horizontal differentiation, consumers have different tastes and thus experience disutility in consuming a standard product which may not match their taste. E.g. consumer A prefers a zero annual fee on a credit card and may not appreciate offers for a credit card with a high annual fee even if the card is better on other attributes such as reward points. On the other hand, consumer B might prefer a card with high rewards even if she has to pay an annual fee. Other customers in this market may have preferences which are intermediate between these two extremes. Thus in this model, consumers have heterogeneous net reservation price for a product, depending on the extent of mismatch between his taste and the product. Offering personalized products increases the utility of different consumers differently. Consumers whose taste match the standard product get a lower increase in utility (because their choice matches closely with the standard product; hence lower disutility due to product mismatch) than consumers whose taste do not match the standard product. Therefore, personalization homogenizes consumers’ reservation price and enables the firm to extract maximum consumer surplus. Adam & Yellen (1976) show that if consumers are more homogenous in their valuations, the seller can extract more consumer surplus (also see Tyagi 2004 for more details).

We consider a market where a fraction of consumers, $\beta$, is privacy conscious and does not allow firms to collect information about them (Acquisti and Varian 2005). These customers, therefore, cannot receive a personalized product. E.g. in a survey by ChoiceStream Inc, only 60% users were willing to share preference information with firms and 46% were willing to share demographic information with firms in exchange for personalized content. The rest of the consumers, $1-\beta$, allow firms to capture information about them and offer them a personalized product. We consider an asymmetric duopoly market in which only one firm, say firm 1, can offer a personalized product to this $1-\beta$ fraction of consumers in the market. We also assume that a firm can offer a personalized product to a customer only if it has information about the customer. While the firm may also need to make complimentary investments in IT to be able to offer a personalized product, we
assume that such costs are essentially fixed and hence we do not consider these in our analysis. Therefore, firm 1 can offer a personalized product for these 1- \( \beta \) consumers which we label as the ‘personalizable segment’ or \( PS \) segment. We label the rest of the customers \( \beta (=1-\alpha) \) as the ‘privacy conscious segment’ or \( PC \) segment (Figure 1). Firm 1 offers a standard product to these customers. In our asymmetric model, firm 2 does not have information about any consumer. Therefore, firm 2 can only offer a standard product to all customers in the market. As discussed earlier, information goods and services have a zero marginal cost of personalization, unlike personalization of physical goods where the marginal cost of personalization may be positive. Once the firm incurs basic setup costs, \( F \), in terms of hardware and software, the marginal cost of personalizing information goods for each additional customer may be negligible (since no new content needs to be created). This assumption is not critical and we later discuss the implication of relaxing this assumption. Finally, we assume that firms do not use personalized pricing.

\[ U = r - p - x \]

\( \alpha, PS \) consumers

Firm 2

\[ U = r - p \] (Dewan et al, 2003)

\( \beta, PC \) consumers

\[ t=1 \}

**Figure 1: Consumer Distribution**

A consumer located at a distance \( x \) from firm 1 receives a utility of \( U = r - p - x \) by using a standard product, where \( r \) is the reservation price and \( p \) is the price charged by firm 1 (standard Hotelling model). ‘\( x \)’ is a measure of the disutility that a consumer experiences due to using a standard product. A personalized product, on the other hand, is tailored to meet the customers’ exact requirements and there are no disutility or misfit costs; hence the utility that a consumer derives from using a personalized product is given as \( U = r-p \) (Dewan et al, 2003). Note that all consumers derive the same utility after using a personalized product, irrespective of their location on the Hotelling line. We also assume that the reservation price is high enough such that all customers buy in equilibrium. Further, we assume a unit transportation cost, i.e., \( t=1 \), which is a standard assumption in horizontal differentiation model (although our results hold for more general value of \( t \)).
We consider the equilibrium under different cases of information sharing and personalization scope selected by firm 1. E.g. firm 1 can select maximal personalization scope (in which it offers a personalized product to all customers in the PS segment) or strategic personalization scope (in which it offers a personalized product to select customers in the PS segment). In fact, maximal personalization scope is a special case of strategic personalization scope in which the firm strategically chooses to offer a personalized product to all customers in the market. The cases we analyze are as follows:

Case 1: No Information Sharing; Maximal Personalization Scope
Case 2: No Information Sharing; Strategic Personalization Scope
Case 3: Information Sharing; Strategic Personalization Scope

2.1 No Information Sharing; Maximal Personalization Scope: In this case, firm 1 can offer a personalized product to all customers in the PS segment and a standard product to customers in the PC segment, whereas firm 2 offers a standard product to all customers. The result is summarized in Proposition 1:

**Proposition 1:** Firm 1 prefers not to personalize even though it has the capability to do so while firm 2 offers standard product. Mathematically, if firm 1 offers a personalized product to all customers in the PS segment, the equilibrium prices and profits are given as follows: $\pi_1 = \frac{(4 - \beta)^2}{18(2 - \beta)}; \pi_2 = \frac{(2 + \beta)^2}{18(2 - \beta)}$; $p_1 = \frac{4 - \beta}{3(2 - \beta)}; p_2 = \frac{2 + \beta}{3(2 - \beta)}$. On the other hand, if both firms offer a standard product to all customers, the equilibrium is as follows: $\pi_1 = \pi_2 = \frac{1}{2}; p_1 = p_2 = 1$.

For proof of all lemmas and propositions (unless otherwise stated), please see the Appendix. Comparing profits of firm 1 in personalization and no-personalization case, it is evident that firm 1 earns lower profits if it offers a personalized product. This result is surprising because it suggests that a firm with the capability to offer a personalized product does not choose to do so even if the competitor cannot personalize. The intuition is as follows: offering a different product to each customer is similar to locating on a continuum along the Hotelling line rather than at a single point. Thus product personalization, in effect, reduces the horizontal differentiation between firms for customers in the PS segment and hence increases price competition.
(negative effect). The firm which personalizes gets a greater market share (positive effect). Overall, we find that the negative effect always dominates the positive effect and both after are worse off after one firm adopts personalization. This is consistent with the results in Ulph et al (2000) who mention that offering personalized pricing makes firms worse off because the ‘intensified competition effect’ dominates the ‘surplus extraction effect’ and hence firm profitability can decrease.

We now consider the case when firm 1 offers a personalized product to select customers in the $PS$ segment; we label this as strategic personalization scope as compared to maximal scope of Section 2.1.

2.2 No Information Sharing; Strategic Personalization Scope: Let $z$ denote the scope of personalization chosen by firm 1, i.e. firm 1 offers a personalized product to a fraction $z$ customers in the $PS$ segment ($0<z<1$); $z=1$ implies maximal personalization scope, as in Section 2.1 above. We assume that this $z$ fraction of customers lies in a continuum close to firm 1; i.e. firm 1 offers a personalized product only to customers who derive a higher value from its products. We model this as a two-stage game as follows: 

**Stage I:** Firm 1 chooses its scope of personalization, $z$. 

**Stage II:** Firms 1 and 2 set respective prices. We use backward induction to solve this game and proceed as follows:

![Figure 2: Game Structure under Strategic Information Scope](image)

**Stage II - Firms choose respective prices, given $z$:** In this stage, firms decide on optimal prices $p_1$ and $p_2$, given that firm 1 offers a personalized product only to a fraction $z$ of consumers in the $PS$ segment in Stage I. Therefore, customers (in the $PS$ segment) to the left of $z$ will experience a disutility due to product misfit if they buy from firm 2. Firm 1 can therefore charge a higher price to these customers. In response to firm 1’s high price, firm 2 can also charge a higher price and capture the $1-z$ fraction of the $PS$ segment. We show that under equilibrium, both firms choose prices such that customers to the left (right) of $z$ always buy from firm
1 (firm 2) and neither firm has incentive to price low enough to capture additional customers in the PS segment. In other words, firms 1 and 2 price such that a fraction \((1-\beta)^* z\) always buys from firm 1 and a fraction \((1-\beta)^* (1- z)\) always buys from firm 2. We label this equilibrium as ‘tacit-collusion’ equilibrium (TCE). Similar to Kim et al (2001), we specify the necessary condition for a pure strategy in such a model as follows: firm 1 specifies \(z\) in the first stage such that firm 1 (firm 2) always captures customers to the left (right) of \(z\) in the second stage. In Stage I, we derive the range of \(z\) such that the TCE is also a non-cooperative Nash equilibrium, i.e., neither firm finds it profitable to deviate by charging lower prices and capturing additional customers in the PS segment. Both firms offer a standard product to customers in the PC segment; therefore the customer located at \(x\left(\frac{p_2 - p_1 + 1}{2}\right)\) in the PC segment is indifferent between buying from either firm. Given that \(\beta\) is the fraction of privacy sensitive customers in the market, the equilibrium is given as:

**Lemma 1:** Given that firm 1 chooses a scope of personalization \(z\) in Stage I, the prices and profits are

\[
p_1^* = \frac{2(1+z) - \beta (2z-1)}{3\beta}; p_2^* = \frac{2(2-z) + \beta (2z-1)}{3\beta}; \pi_1 = \frac{(2(1+z) - \beta (2z-1))^2}{18\beta}; \pi_2 = \frac{(2(2-z) + \beta (2z-1))^2}{18\beta}.
\]

Under this lemma, price charged by firm 1 (firm 2) increases (decreases) with increase in \(z\) (firm 1’s scope of personalization). Also, \(\frac{\partial \pi_1}{\partial z} > 0, \frac{\partial \pi_2}{\partial z} < 0\), i.e., for a given value of \(\beta\), firm 1 earns a higher profit as \(z\) increases. This is intuitive since an increase in \(z\) implies that a bigger fraction of customers in the PS segment always buys from firm. Firm 1 can charge a higher price to extract a higher surplus from these customers at the expense of losing customers who receive a non-personalized product.

**Stage I – Firm 1 chooses scope of personalization, \(z\):**

From lemma 1 above, \(\frac{\partial \pi_1}{\partial z} > 0\); ideally, firm 1 should select maximal personalization scope. However, a large value of \(z\) implies that firm 2’s share of the PS segment (equal to \((1-\beta)^* (1- z)\)) reduces and hence firm 2’s profit as well, i.e., \(\frac{\partial \pi_2}{\partial z} < 0\). It is likely that as \(z\) increases beyond a certain critical value (\(=z^*\)), firm 2’s
profit under TCE reduces so much that it might find it profitable to deviate from the TCE by pricing low to capture additional customers to the left of \( z \). In that case, the Nash equilibrium breaks down and no pure strategy equilibrium exists. Similarly, if \( z \) is small enough, firm 1 might find it profitable to deviate by charging a low price and capturing customers to the right of \( z \). For a non-cooperative Nash equilibrium to exist, the following conditions should be satisfied:

i. **IC1:** Firm 1 does not find it profitable to deviate by charging a price \( p_1 (< p_1^*) \) and capturing customers to the right of \( z \).

ii. **IC2:** Firm 2 does not find it profitable to deviate by charging a price \( p_2 (< p_2^*) \) and capturing customers to the left of \( z \).

Note that firm 1 offers a personalized product to customers to the left of \( z \), whereas firm 2 offers a standard product to customers to the right of \( z \). In other words, it is easier for firm 1 to capture additional customers to the right of \( z \) than it is for firm 2 to capture customers to the left of \( z \). Solving the incentive compatibility condition for firm 2, we get the following lemma:

**Lemma 2:** Firm 2 finds it profitable to deviate from the tacit collusion equilibrium if firm 1 personalizes for more than a fraction \( z^* \) of customers in the PS segment.

Mathematically, \( z^* = \frac{4 + \beta (14 - \beta (10 - \beta)) - 3 (4 - \beta (2 - \beta)) \sqrt{\beta (2 - \beta)}}{(2 - \beta) (1 - \beta) (5 \beta - 2)} \).

However, if firm 1 chooses a personalization scope \( z \) such that \( ((1-\beta)^*z) \) is less than a certain threshold, firm 1 can find it optimal to deviate from the Nash equilibrium by lowering its price to capture additional customers to the right of \( z \). We label this minimum threshold of \( z \) as \( z^{**} \). This can be summarized as:

**Lemma 3:** If \( z \) is less than a critical value \( (z^{**}) \), firm 1 finds it optimal to deviate from the Nash equilibrium.

The above lemma follows from the incentive compatibility condition of firm 1. Mathematically, \( z^{**} = \frac{2 + \beta}{1 + 2 \beta + 3 \sqrt{\beta}} \). Further \( \frac{\partial z^*}{\partial \beta} > 0; \frac{\partial z^{**}}{\partial \beta} < 0 \).
Combining Lemmas 2 and 3, we observe that for tacit collusion equilibrium firm to hold, firm 1 restricts its scope of personalization to $z^*$, subject to $z^* > z^{**}$. Solving for $\beta$ in $z^* = z^{**}$, we note that the condition under which $z^* > z^{**}$ is when $\beta > 0.59$. This is shown in Figure 3a below:

\[
\begin{array}{c}
0 & 0.59 & \beta \rightarrow & 1 \\
\end{array}
\]

**Figure 3a: Equilibrium for range of $\beta$ under no Information Sharing**

**Proposition 2:** Under the condition that $\beta > 0.59$, firm 1 will restrict its personalization scope and chooses to offer a personalized product to only a fraction $z^*$ of the PS segment. Overall, increase in fraction of privacy conscious customers leads to a decrease in both firms’ profits, i.e. $\frac{\partial \pi_i}{\partial \beta} < 0$. For $\beta < 0.59$, both firms offer a standard product and the equilibrium is the same as in Proposition 1.

This proposition suggests that the optimal strategic scope of personalization that firm 1 chooses is less than the maximal scope, i.e. $z^* < 1$. This is an interesting observation because even though we assume that the cost of personalizing for each additional customer is zero, we find that firm 1 will offer a personalized product to select customers in the market. The intuition is that maximal personalization by one firm destroys rather than creates economic value for either firm because overall price competition in the market increases. However, personalizing for select customers creates a disincentive for these customers to buy from a firm which offers a standard product. Hence both firms can charge higher prices, which results in virtual monopoly for both firms and consequently higher profits.

Figure 3b shows the profits of both firms for different values of $\beta$. Profits for both firms are higher for higher values of $\beta$. This is surprising because it implies that both firms earn higher profits when a fraction of consumers is privacy sensitive. The intuition is that too few privacy sensitive customers (in other words, if a bigger fraction prefers a personalized product) leads to higher prices by both firms such that it becomes easier for one firm to price lower and deviate from the Nash equilibrium. Therefore, the TCE which enables
both firms to earn higher profits is not feasible when the fraction of privacy sensitive customers is below a certain threshold.

Also, for $\beta > 0.59$, $\frac{\partial \pi_i}{\partial \beta} < 0$ suggesting that the profits for both firms decrease as the fraction of privacy sensitive customers in the market increases. The intuition is that increase in $\beta$ leads to a decrease in the overall size of the PS segment, since firms 1 and 2 have an assured market share of $(1-\beta)z^*$ and $(1-\beta)(1-z^*)$ respectively under the tacit collusion equilibrium. This leads to an increase in price competition and hence lower profits for both firms.

Thus under this ‘tacit collusion’ Nash equilibrium, neither firm finds it optimal to price low and capture the other firm’s personalized customers. Kim, Shi and Srinivasan (2000) also suggest similar tacit collusion equilibrium when a group of consumers experiences switching costs when firms offer rewards programs (e.g. airline miles).

2.2.1 Relaxing the assumption of zero marginal cost of personalization

In the prior section, we assumed that the marginal cost of personalization is zero. In this section, we provide an outline on how a non-zero cost of personalization could impact our results. Consider a model with non-zero marginal costs of personalization. In general, let the cost of personalization be $C = c(z)$ where $z$ is
the scope of personalization. We assume a convex and twice differentiable increasing cost function such that 
\( c' > 0 \) and \( c'' \geq 0 \). Rewriting the profit functions of both firms, 
\( \pi_1^{Net} = \pi_1(z) - c(z) \); \( \pi_2^{Net} = \pi_2(z) \) where 
\( \pi_1(z) \) and \( \pi_2(z) \) are the firms’ profits as a function of \( z \), as given in lemma 1.

For \( c(z) = 0 \) (i.e. zero cost of personalization), the optimal scope of personalization is as given in 
proposition 2, i.e. \( z = z^* \). For non-zero costs of personalization, we can solve for \( z \) as follows: from 
proposition 2, we can verify that \( \frac{\partial \pi_1}{\partial z} > 0 \) and \( \frac{\partial^2 \pi_1}{\partial z^2} < 0 \). Further, we assume that \( \frac{\partial c}{\partial z} > 0 \) and \( \frac{\partial^2 c}{\partial z^2} > 0 \).

Since \( \pi_1'(z = 0) > 0 \) and \( c'(z = 0) = 0 \), there exists at most one value of \( l > z > 0 \) where \( \pi_1'(z) = c'(z) \). Let \( z' \) be 
the value of \( z \) where the marginal benefit of increasing the scope of personalization is just equal to the 
marginal cost of personalizing for an additional customer. The result can be summarized in the following 
corollary:

**Corollary 1:** Given a non-zero and convex cost of personalization \( c(z) \), firm 1 chooses an optimal scope 
of personalization as \( z = \text{Min} (z_c, z^*) \) if \( z' > z^{**} \).

The intuition is as follows: if \( z' > z^* \), the optimal scope of personalization that firm 1 chooses is \( z^* \) (any 
value of \( z > z^* \) is not a Nash equilibrium – lemma 2). On the other hand, if \( z' < z^* \), firm 1 would not choose to 
expand its scope beyond \( z' \) because the marginal benefit of personalizing is less than the marginal cost.

### 2.3 Information Sharing; Strategic Personalization Scope:

Consider the scenario where firm 1 transfers information about a fraction of consumers \((1- x_0)\) to firm 2 
(out of the PS segment). We use the terms ‘information sharing’ and ‘information transfer’ interchangeably 
in our analysis. After the information transfer, firm 2 can offer a personalized product to \((1- x_0)\) consumers 
out of the PS segment. While it is true that firm 2 might require complementary investments in IT to be able 
to personalize (even after it receives consumer information from firm 1), we consider the costs of such 
investments as essentially fixed and hence exclude them from our analysis. We examine the case when firm 
1 shares information about a continuum of consumers located further away from it (closer to firm 2). E.g.

---

*If \( z' > z^* \), the optimal scope of personalization that firm 1 chooses is \( z^* \) (any value of \( z > z^* \) is not a Nash equilibrium – lemma 2). If \( z' < z^* \), firm 1 would not choose to expand its scope beyond \( z' \) because the marginal benefit of personalizing is less than the marginal cost.*

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Catalog Age (July 2000 Page 41) reported that direct marketers, who participate in information sharing agreements, may not share information about their best customers (who have the highest valuation for their product). In this game, we assume that firm 1 restricts its scope of personalization \( z = x_0 \), i.e., firm 1 chooses to offer a standard product to customers whose information it shares with firm 2. We can show that \( z = x_0 \) weakly dominates both \( z > x_0 \) or \( z < x_0 \). We set this the game as follows:

Stage I  
Firm 1 selects 1- \( x_0 \), i.e. amount of information transferred to firm 2

Stage II  
Firms 1 and 2 set prices

**Figure 4: Game Structure under Information Sharing**

This game is similar to that in section 2.2. We solve for tacit collusion Nash equilibrium where firm 1 offers a personalized product to \( x_0 \) customers in the PS segment and a standard product to the rest of the customers in the PS and PC segments. Firm 2 offers a personalized product to 1- \( x_0 \) customers in the PS segment and a standard product to the rest of the customers. Similar to the previous section, we use backward induction to solve our two-stage model for equilibrium prices and optimal amount of information shared by firm 1.

**Lemma 4:** Given that firm 1 shares information about 1- \( x_0 \) customers with firm 2, the equilibrium prices and profit are given as follows:

\[
p_1 = \frac{2 + 2x_0 + \beta - 2x_0 \beta}{3 \beta}; p_2 = \frac{4 + 2x_0 + \beta - 2x_0 \beta}{3 \beta}; \pi_1 = \frac{(2 + 2x_0 + \beta - 2x_0 \beta)^2}{18 \beta}; \pi_2 = \frac{(4 + 2x_0 + \beta - 2x_0 \beta)^2}{18 \beta}
\]

This result is similar to lemma 1, except that the equilibrium is characterized in terms of the amount of information shared.

Moving on to the first stage, we look at the incentive compatibility conditions (ICC) for both firms. The ICC for firm 2 remains same, i.e., we check whether firm 2 can find it profitable to deviate from the TCE by capturing customers to the left of \( x_0 \) who receive a personalized product from firm 1.

**Lemma 5:** If the amount of information shared by firm 1 is less than a minimum threshold 1- \( x_0^* \), firm 2 finds it profitable to deviate by charging a lower price.

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Mathematically, \( x_0^* = \frac{4 + \beta (14 - \beta (10 - \beta)) - 3(4 - \beta (2 - \beta))\sqrt{\beta (2 - \beta)}}{(2 - \beta)(1 - \beta)(5\beta - 2)} \). Please refer to the Appendix for calculation of \( x_0^* \), which are similar to that of \( z^* \) since the incentive compatibility conditions for firm 2 do not change compared to the previous section. However, the ICC condition for firm 1 is different than in the previous section. Now if firm 1 wants to deviate from the \( TCE \), it has to capture customers to the right of \( x_0^* \) who now receive a personalized product from firm 2. In other words, deviating from the tacit collusion equilibrium is more difficult for firm 1 than in section 2.2 because firm 2 now offers a personalized product to customers located to the right of \( x_0^* \). Since both firm 1 and firm 2 offer a personalized product, the ICC conditions for both firms are similar. It is intuitive that pure strategy Nash equilibrium exists only if \( x_0^* > \frac{1}{2} \). A value of \( x_0^* < \frac{1}{2} \) implies that firm 2 requires more than half the size of the PS segment to not deviate from the tacit collusion equilibrium (\( TCE \)). By similar reasoning, firm 1 also needs more than half the market under the \( TCE \) and hence, no equilibrium is possible.

**Lemma 6:** Firm 1 does not find it profitable to deviate from the tacit collusion equilibrium for \( x_0^* > \frac{1}{2} \).

Combining the results in lemmas 4 and 5, the Nash equilibrium for the information sharing game is as follows:

**Proposition 3:** Under the condition that \( \beta > 0.51 \), there exists a pure strategy Nash equilibrium under which firm 1 finds it optimal to transfer information about a fraction \( 1-x_0^* \) of customers in the PS segment to firm 2, where

\[
x_0^* = \frac{4 + \beta (14 - \beta (10 - \beta)) - 3(4 - \beta (2 - \beta))\sqrt{\beta (2 - \beta)}}{(2 - \beta)(1 - \beta)(5\beta - 2)}.
\]

Comparing Propositions 2 and 3, we find that under information sharing, \( TCE \) is the equilibrium for a larger range of \( \beta \) values (\( \beta > 0.51 \)) than under no-information sharing (\( \beta > 0.59 \)). In other words, firm 1 earns at least as much profit under information sharing as under no-information sharing for different values of \( \beta \).

**Corollary 1:** Sharing information with firm 2 is a weakly dominating strategy for firm 1.

This follows directly from the above two propositions. Profits of firm 1 remain the same with or without information sharing for \( \beta < 0.51 \) and \( \beta > 0.59 \). However, \( 0.51 < \beta < 0.59 \), profits of firm 1 are lower without
information sharing since the tacit collusion equilibrium holds in this region only if firm 1 shares information with firm 2. This is as shown in Figure 5.

![Figure 5: Firm 1’s Profits as a function of $\beta$ with and without information sharing](image)

### 3. Consumer Surplus and Information Sharing

Next, we calculate the consumer surplus under information sharing and also under no information sharing. We express the consumer surplus as a function of $\beta$, the fraction of privacy conscious customers in the market. The results can be summed up as follows:

**Proposition 4:** Consumer Surplus can increase or decrease with information sharing, depending on $\beta$.

For $\beta < 0.51$, consumer surplus is the same with or without information sharing. For $0.51 < \beta < 0.59$, consumer surplus is higher without information sharing than with information sharing. Finally, for $\beta > 0.59$, consumer surplus is higher if firms share information than if firms do not share information.

For $\beta < 0.51$, TCE is not possible; therefore, both firms offer a standard product to all customers and consumer surplus is the same in all three cases. On the other hand, TCE is possible only with information sharing for $0.51 < \beta < 0.59$; therefore, firm 1 offers a personalized product to some customers in the $PS$ segment and charges a higher price. Therefore, consumer surplus is lower with information sharing than with no information sharing in this case. Finally, for $\beta > 0.59$, TCE is possible both with and without information sharing.
sharing. Therefore, consumer surplus is higher with information sharing because firm 2 can also offer a personalized product which increases consumer utility. This can be shown graphically as follows:

![Figure 6](image-url)  
**Figure 6: Consumer Surplus as a function of $\beta$ in three cases:**  
a. no personalization  
b. strategic personalization scope, no information sharing  
c. information sharing

Figure 6 suggests another interesting result. Consumer surplus is the highest when the fraction of privacy sensitive customers in the market is low ($\beta < 0.51$). This happens because low values of $\beta$ lead to higher values of $p_1$ and $p_2$, i.e. $\frac{\partial p_i}{\partial \beta} < 0$. The TCE is not sustainable for high values of $p_1$ and $p_2$ because either firm can find it optimal to deviate by charging a lower price. Thus, presence of privacy conscious can lead to lower consumer surplus because it leads to additional segmentation in the market and enables firms to charge higher prices.

Next we compare the surplus of the PS and PC segments with that in the no-personalization case.

**Corollary 1:** Privacy sensitive customers always earn a lower surplus when firm 1 personalizes than in the no-personalization case. Also, customers in the PS segment may earn a higher surplus than the no-personalization case if $\beta > 0.81$.

In other words, for higher values of $\beta$, consumers who receive a personalized product get a higher surplus at the expense of privacy sensitive customers. The intuition is that for higher values of $\beta$, prices $p_i$
and $p_2$ decrease till the increased surplus effect due to personalization dominates the decreased utility due to increased price.

4. Information Ownership

So far in our analysis, we assumed that firm 1 owns information about the PS segment and decides whether or not to share the same with firm 2. However, research suggests that consumers like to control how firms collect and use information about them. E.g. Westin (1967) defines privacy as the ability of individuals to control the terms under which personal information is collected and used. Nowak and Phelps (1995) suggest that consumers’ privacy could be violated if the information collected for one purpose is subsequently used for a different purpose without the knowledge or consent of the consumer. For this reason, firms are making an effort to make consumers better informed about their practices regarding collection and distribution of information. E.g. many websites provide a check-box which the customers can check if they want to allow the firm to share their information with third parties (opt-in). Some firms such as Doubleclick follow an opt-out policy where it is the consumer’s responsibility to notify the firm to prevent it from sharing her information with other marketers. In this section, we analyze the case when consumers own their information and decide whether to allow the firm to share their information with other firms. Here we consider only the ownership rights of the PS segment of consumers since neither of the firms has information about the PC segment. The game proceeds as shown in Figure 7:

![Figure 7: Game Structure for Information Ownership Model](image)

We use backward induction to solve for equilibrium in this three stage game.
**Stage III: Firms decide on respective prices**

Similar to the last section, we model the equilibrium as a tacit collusion in prices and derive conditions under which neither firm chooses to deviate from this equilibrium. As in section 3, firm prices depend only on \( x^*_0 \), where \( 1-x^*_0 \) is the amount of information transferred by firm 1 to firm 2 in stage II. Therefore prices are the same as given in proposition 3.

**Stage II: Firm 1 decides on how much information to share**

In section 2.3, we showed the amount of information shared by firm 1 should satisfy incentive compatibility conditions IC1 and IC2. Now we have to consider additional restrictions because the amount of information that firm 1 shares with firm 2 also depends on the number of customers who allow firm 1 to share their information. Let firm 1 share \( 1-x^*_0 \) (\( >0 \)) information with firm 2. \( 1-x^*_0 =0 \) implies that no information sharing takes place. Let \( y_0 \) denote the fraction of customers in the PS segment who allow firm 1 to share their information with firm 2, i.e. these customers derive a higher surplus from a standard product at a lower price (as in proposition 1) than a personalized product at a higher price (as in proposition 3). In stage I, we shall show that these \( y_0 \) customers are located in a continuum close to firm 2 (define \( y^* = 1-y_0 \), such that \( y^* \) is the location of the indifferent customer).

**Lemma 7:**

- If all customers allow firm 1 to share their information with firm 2 (\( y^*=1 \)), the equilibrium is as given in Proposition 3.
- If none of the customers allows firm 1 to share information with firm 2 (\( y^*=0 \)), the equilibrium is as given in Proposition 2.

For intermediate values of \( y^* \), we derive the equilibrium as follows:

1. \( y^*< x^*_0 \): in this case, less number of customers are willing to allow information sharing than the minimum required for the tacit collusion equilibrium. Therefore, no information sharing is possible since the customers to the right to \( x^*_0 \) do not allow firm 1 to share information with firm 2. If no information sharing takes place, two types of equilibriums are possible - when \( x^*_0 > z^{**} \), tacit collusion is possible without information sharing (proposition 2); when \( x^*_0 < z^{**} \), no tacit collusion is possible because firm 1 can find it
profitable to deviate by capturing additional customers to the right of \( x_0^* \). The value of \( z^{**} \) is given in lemma 3.

2. \( y^* > x_0^* \): here firm 1 can transfer information about only \( y_0 - x_0^* \) customer to firm 2. As in section 3.2, we assume that firm 1 offers a personalized product only to customers to the left of \( x_0^* \). Therefore, firm 2 offers a personalized product to \( y^* - x_0^* \) customers to the right of \( x_0^* \) and the rest \( 1 - y^* \) customers do not receive a personalized product.

We can re-write this in form of the following lemma:

**Lemma 8:** The amount of information shared by firm 1 depends on \( z^{**}, x_0^* \) and \( y^* \):

- If \( 1 > y^* > x_0^* \), firm 1 always offers a personalized product to customers to the left of \( x_0^* \) and shares \( y^* - x_0^* \) information with firm 2. None of the firms finds it profitable to deviate from the tacit collusion equilibrium. This is represented in Figure 8a.

- If \( y^* < x_0^* \) and \( x_0^* > z^{**} \), firm 1 always offers a personalized product to customers to the left of \( x_0^* \) and does not share any information with firm 2. However, the tacit collusion equilibrium holds and prices are the same as in proposition 2 (no information sharing case) (Figure 8b).

- \( y^* < x_0^* \) and \( x_0^* < z^{**} \), firm 1 does not share any information with firm 2 and the tacit collusion equilibrium does not hold as both firms have an incentive to deviate. Therefore, no firm offers a personalized product and the equilibrium is the same as in proposition 1 (Figure 8c).

**Stage I:** Each consumer decides whether to allow information transfer

In this stage, we first calculate \( y^* \), which represents the marginal customer in the PS segment who is indifferent to allowing information sharing; i.e. the customer at \( y^* \) gets the same utility if she receive a
personalized product at a higher price or a standard product at a lower price. Consider two customers located at \( x_1 \) and \( x_2 \) on the Hotelling line such that \( x_1 > x_2 \). Clearly, a customer located close to firm 2 has a higher utility for a standard product at a lower price than a customer farther away from firm 2 because her disutility with firm 2’s standard product is lower. On the other hand, a customer located farther away from firm 2 has a higher utility for a personalized product than a customer located closer to firm 2.

When both firms offer a standard product (no TCE), the welfare of a consumer from the PS segment located at \( y \) (at a distance \( 1-y \) from firm 2) and buying from firm 2 is given as \( U_2' = r - p_2' - I + y \). After information sharing, the welfare of the consumer who buys from firm 2 is given as \( U_2 = r - p_2 \).\(^9\) (The difference in the utility functions arises because firm 2 can now offer a personalized product; therefore the customer experiences no disutility due to the distance \( y \)). A customer agrees to information sharing if \( U_2 > U_2' \). Solving for \( y \), we get \( y^* < p_2' - p_2 + l \) where \( y^* \) gives the value of \( y \) such that customer to the left of \( y^* \) are willing to allow firm 1 to share their information with firm 2.

**Lemma 9:** Customers to the left of \( y^* \) derive a higher utility from using a personalized product at a higher price as compared to a standard product at a lower price.

Mathematically, \( y^* = 1 - \frac{\beta \left( 16 - \beta (28 - 11\beta) - 2(4 - (4 - (2 - \beta)\beta))\sqrt{(2 - \beta)\beta} \right)}{(2 - \beta)(5\beta - 2)\beta} \). Proof of the lemma follows by substituting the values of \( x_0^* \), \( p_2' \) and \( p_2 \) in the inequality \( U_2 > U_2' \). Customers to the right of \( y^* \) prefer to receive a standard product from firm 2 at a lower price than a personalized product at a higher price. However, from Figure 8(a) and 8(b), we observe that under some conditions, firm 2 can still charge customers a higher price (tacit collusion equilibrium) even if it offers a standard product. Therefore, under some conditions, the firms’ decision to charge higher prices is independent of whether customers allow information sharing or not. Under such a scenario, customers to the right of \( y^* \) prefer to receive a personalized product from firm 2 instead of a standard product. Therefore, customers to the right of \( y^* \) also allow information sharing. In short, the customers’ decision to share information is based on the following incentive compatibility rule:

\(^9\) \( p_2' \) and \( p_2 \) are the prices charged by firm 2 as given in propositions 1 and 3 respectively.
**Lemma 10: IC Rule:** If tacit collusion equilibrium is the outcome in stage II regardless of information sharing, then all customers in the PS segment prefer to allow information sharing irrespective of $y^*$. 

From proposition 2, $TCE$ is always possible for $\beta > 0.59$, irrespective of information sharing. Thus, this represents a region of **non-credible threat** in which $TCE$ is the equilibrium irrespective of whether customers allow information sharing or not. Therefore customers to the right of $y^*$, who prefer a standard product from firm 2 at a lower price, allow firm 1 to share their information with firm 2. On the other hand, if information sharing is required for $TCE$ (for $0.51 < \beta < 0.59$), customers to the right of $y_0$ do not allow information sharing and the tacit collusion equilibrium is not stable; in this case, the equilibrium is the same as given in proposition 1. Thus this represents a region of **credible threat** in which customers prevent firm 1 from sharing information with firm 2. This can be summed up in the following proposition.

![Figure 9: Consumer Surplus under different information ownership structures](image)

**Proposition 5:**

- All customers allow information sharing if $y^* < x_0^*$ and $x_0^* > z^{**}$ or if $y^* > x_0^*$. In this case, the equilibrium prices are the same as in proposition 2.
- On the other hand, if $y^* < x_0^*$ and $x_0^* < z^{**}$, customers to the right of $y^*$ do not allow information sharing and the equilibrium prices are given in proposition 1.
- Consumer surplus remains the same or increases when consumers have information ownership.
Proof of this proposition follows from the preceding discussion. We can verify that this is indeed Nash equilibrium and neither firms nor customers find it optimal to deviate from this equilibrium. In short, consumer surplus is at least as high when consumers have information ownership than when firms have information ownership.

5. Conclusions

In this research, we extend existing research on information sharing to model the practice of information sharing among online firms when consumer information is used to offer a personalized product. We use a model of horizontal product differentiation where consumers differ in taste attributes; personalization eliminates the disutility that consumers experience in using a standard product by serving each consumer exactly the product that matches her taste (Dewan et al 2003). We use a model of asymmetric duopoly in our study where only one firm has information about a fraction of consumers in the market and the other firm does not. We also allow for the possibility that a fraction of customers is not known to either firm (we label these as privacy conscious customers who either do not provide information to firms or routinely delete cookies so that firms cannot keep track of their browsing patterns and consequently cannot develop a product preference profile for such customers.). We confirm existing theory that personalization (serving different products to different customers) may not be profitable when firms are ex-ante horizontally differentiated because serving multiple products on the Hotelling line reduces the horizontal differentiation between firms and leads to lower profits. However, personalization is profitable if a firm can restrict its scope of personalization by personalizing for select customers rather for all customers in the market – i.e. firms should choose a strategic scope of personalization rather than maximal personalization. This is especially interesting considering the fact that we assume the marginal costs of personalization for information goods to be zero. Similar insights are shared in a report by Aberdeen group which suggests that a firm should personalize for high value customers only and not for everyone.

An interesting result of our paper is that presence of privacy conscious customers can lead to higher profits for both firms (and lower consumer surplus) under some conditions. The reason is that presence of privacy sensitive customers creates different consumer segments in the market (privacy sensitive and non-
privacy sensitive customers) and firms can take advantage of this by offering a personalized product to the non-privacy sensitive customers and a standard product to the privacy sensitive customers. Personalizing for select customers creates switching costs for these consumers which enables both firms to price higher and earn higher profits than under no-personalization.

We find that that under some conditions, the firm with consumer information can share information about a fraction of consumers with the other firm and that information sharing is a weakly dominant strategy for a firm than no-information sharing. We find that information sharing between firms leads to increased consumer surplus if the fraction of privacy conscious customers is greater than a certain threshold. We also examine the case where consumers possess the ownership of their information and decide whether to allow a firm to share their information with other firms. We examine the case where consumers possess ownership over their information and decide whether firm 1 can share their information with firm 2 or not. We show that, under some conditions, information ownership poses a credible threat because consumers choose not to allow information sharing and both firms offer a standard product. On the other hand, there exists certain regions in our equilibrium where consumer information ownership poses a non-credible threat because consumer who are worse off after personalization still choose to allow firms to share their information.

Overall, our research highlights the economics of information sharing related to personalization of information goods and personalization of non-product attributes of physical goods sold online. Information sharing has been a salient feature of direct marketing for a long time. Our research provides guidelines to managers about when and how much information to share and also insight to policy makers about the welfare implications of information sharing.

**Limitations**

The main limitation of this research is that out model mainly applies to cases where the aim of the personalization technology is to provide a different product to different customers. In terms of economic modeling, this is similar to the concept of product proliferation (Dewan et al 2003). Personalization is a broad term which includes practices such as targeted banner advertisements, customization and targeted couponing. Different economic models could be suited to represent different types of personalization. E.g.
targeted advertisement can be has been captured in the works of Chen et al, 2001 using a probability model. Another limitation of the model is that the products are assumed to be substitutes; future research can extend the model to analyze the case when firm 1 and firm 2 offer complementary products.
Essay 3: Examining the Personalization-Privacy Tradeoff – an Empirical Investigation with Email Advertisements

"Many companies do not know what personalization can do for them or even precisely what it is -- but that did not stop them from throwing money at the idea when the economy was soaring." crmdaily.com

1. Introduction

Personalization is defined as the use of information technology to tailor customer interactions on an individual basis across sales, marketing and customer service. It is a key technology in both B2B and B2C ecommerce and includes a variety of practices such as online recommendations (Amazon.com), customization (mywashingtonpost.com) and targeted advertising (Yesmail.com) (Ansari & Mela 2003, Murthi & Sarkar 2003). Internet personalization offers the promise of a shopping environment reminiscent of the pre-industrial revolution era – when most businesses were neighborhood stores and the owners greeted each customer by name and also knew what each customer liked. To achieve this end, firms need information about consumers to provide personalized products and services – one, personal information such as name, demographics and location; and two, information about customers’ product preferences. Firms gather this information either during an initial transaction (e.g., when a customer registers with the firm), by observing consumers’ buying and browsing patterns subsequently or by buying consumer information from other firms or third party databases.

Personalization provides benefits to consumers by treating each customer individually and giving them the right product/information at the right time. However, use of consumer information can cause various concerns among consumers, the chief among which is violation of privacy. E.g., Malhotra et al (2004) label consumer information as a double edged sword – which can enhance consumer utility, and at the same time can be misused to cause privacy violation. The hue and cry over cases such as Lotus, Blockbuster (Culnan 1993) and DoubleClick (Culnan and Bies 2003) highlights the importance of respecting consumer privacy.

While it has been established that most consumers would like firms to respect their privacy, it is not clear whether consumers who spend time and effort to protect their own privacy. Anecdotal evidence suggests that there is a wide gap between consumers’ stated and actual privacy concerns. Austin Hill, a leading privacy expert summarizes this gap as follows: “If you ask a roomful of 100 people whether they care about online
privacy, 80 people will raise their hands, he says. If you ask the same roomful of people if they are willing to donate a DNA sample in exchange for a free Big Mac, 80 people will raise their hands.”

Surveys by ecommerce vendors and independent research organizations suggest that consumers routinely provide information such as date of birth, household income and other personal details to access an online service (e.g., open a hotmail account). A survey among consumers suggested that less than 40% read privacy policies and more than 90% do not delete first party cookies. Apart from privacy concerns, consumers may not always respond favorably to personalization due to the following additional factors: one, the recommendations are not always correct because incomplete information and technology limitations make it difficult to predict what products a consumer would be interested in at any given moment. Two, consumers may also be turned off when a firm asks too many questions in the name of personalization. Finally, personalization may sometimes increase the complexity and reduce performance because websites which offer personalization have to generate dynamic content each time a customer requests some information.

For a summary of prior work in management science and economics on personalization, please refer to Murthy and Sarkar (2003). Chen et al (2002) find no evidence of beneficial consumer behavior due to personalization in their empirical study with online brokerages. Prior analytical research (Chen et al 2001, Shaffer and Zhang 1995, Dewan, Jing and Seidmann 2003) captures the strategic impact of personalization in terms of price competition and strategic entry-exit. These studies do not model the consumer disutility due to privacy concerns and assume that consumers always derive a higher utility from personalization. Overall, there is no clear empirical evidence of whether consumers prefer personalization or whether privacy or other concerns lead to a negative response to personalization. With this motivation, we propose our research questions as follows: one, how do consumers react when firms use their information to offer a personalized product or service? Two, how heterogeneous is consumer response to personalization? Can we classify consumers into identifiable segments which differ in their response towards personalization?

We collect a unique data set of responses to ten million emails sent to over 600,000 customers between April-Dec 2002, from a web-based firm. The firm used two levels of personalization - one, sending emails to

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customers about products that they expressed an interest in the past (which we label as *product based personalization*) and two, greeting the customers by name (which we label as *personalized greeting*). The interesting aspect of this data is that the setting in which this data was collected is very similar to a natural experiment in which customers received personalized as well as non-personalized emails at random. Any concerns about personalization would be reflected in the response rates. We define the response to an email advertisement in terms of four levels: opening, unsubscripton, click-through and purchase. We test our hypothesis using a multi-stage ordered probit model in a hierarchical Bayesian framework to estimate individual level parameters. The main results of our study are: one, we show that customers respond positively to product-based personalization but negatively to personalized greetings. A possible reason to this difference in response to different types of personalization is that customers are more likely to perceive a privacy violation when they see their name in an email advertisement. We also find that using both product-based personalization and personalized greetings in an email advertisement, on average, leads to a more positive response than personalized greeting. Customers differ in their response when firms use both personalized greetings and product-based personalization. While consumers who are more likely to make a purchase prefer emails where personalized greetings are accompanied by targeted product recommendations, most customers either react negatively or at best are indifferent to emails with both types of personalization. Overall, we show that customers differ significantly in their preference for different types of personalization and that firms should use ‘personalized’ personalization (where firms target different customers with different levels of personalization) rather than *all-inclusive* personalization (in which each advertisement is personalized at multiple levels).

Our results also highlight significant differences between consumers in terms of their response to personalized emails based on observable characteristics such as **i.** whether the customers’ information is purchased from outside (*acquired customers*) or whether the customers registered with the firm on their own (*organic customers*) and **ii.** whether the customers made any purchase with the firm prior to our data collection. We find that *acquired* customers always react negatively to personalized greetings, even if the greetings are followed by targeted product recommendations. However, customers who make a prior
purchase are no different from customers who made no prior purchase in terms of response to personalized greetings. We also find that *acquired* customers are more likely to open an email but less likely to make a click-through or purchase as compared to *organic* customers. On the other hand, customers who made prior purchases with the firm have a lower chance of unsubscribing and a higher chance of opening and making a click-through than customers who made no prior purchases.

A key contribution of our paper is that this is one of the first studies to analyze consumers’ response to email advertisement using real world data and to develop a model to test how consumers’ respond to firms’ use of information for personalization. We use a methodology that allows us to estimate parameters at an individual level and thus allows us to estimate the individual user response which is key to interesting managerial insights. Our analysis has implications beyond suggesting that personalization generates a positive economic value for a firm. We suggest evidence of privacy concerns among consumers by using response to personalized greetings as a proxy for consumer privacy, and also highlight cases where personalization may or may not deliver significant value for a firm. Individual level estimates also help us generate additional insights into consumer behavior towards personalized email advertisements and we find that consumers differ significantly in their response to personalization, and that firms must respond with different types and levels of personalization for different consumers.

The rest of the paper is organized as follows: in section 2, we propose a conceptual model of how consumers are likely to respond when a firm uses different types of information for personalization. In section 3, we describe our data in detail and in section 4, we develop our hypothesis. We present our mathematical model in Section 5 and in section 6, we highlight the results of our model. Finally, in section 7, we present our conclusions, highlight the limitations of our study and propose areas of future research.

2. Consumers’ Response to Use of Information

As suggested earlier, there are various factors which govern consumers’ response to personalization. We first examine the relationship between firms’ use of information for personalization and consumer privacy. Use of information for personalization is likely to lead to privacy concerns for consumers. Past research on consumer privacy, primarily in the areas of consumer behavior and psychology, has attempted to define
privacy and what constitutes privacy for different individuals. In this section, we present a brief review of the theory behind privacy and discuss the constructs of user privacy in email advertisements. The earliest definition of privacy dates back to 1890 when Warren and Brandeis (1890) referred to privacy as the “right of an individual to be left alone”. In the context of direct marketing, Westin (1967) defines privacy as the ability of individuals to control the terms under which personal information is collected and used. Dufree et al, (1999) propose a ‘social contract’ theory of privacy wherein exchange of information between a consumer and a firm is viewed as an implicit contract and any use of this information by the firm without the knowledge and consent of the consumer constitutes a breach to the contract.

Recently, there have been many attempts to ensure better consumer privacy on the internet. The CAN-SPAM Act of 2003 establishes guidelines for firms sending advertisements via email. As a result of these efforts, there is a marked increase in consumer awareness about privacy related issues and firms are taking steps to comply with commonly accepted privacy practices (such as those specified in the CAN-SPAM Act). E.g., websites include detailed privacy policies mentioning how firms will collect, use, and share consumer information with third parties. Emails have a link at the bottom giving consumers the option of unsubscribing from the firms’ mailing list. The CAN-SPAM Act prohibits deceptive subject line and false or misleading header information. The FTC also provides guidelines on how firms can take steps to better protect consumer privacy. It proposes five major steps, also known as ‘fair information practice codes’. These are: Notice/Awareness, Choice/Consent, Access/Participation, Integrity/Security, and Enforcement/Redress.\footnote{More details on these five steps are provided on the FTC website - \url{http://www.ftc.gov/reports/privacy3/fairinfo.htm}}

Several studies have attempted to formalize constructs to measure consumers’ privacy concerns. One of the earliest such attempts was made by Smith et al (1996) who proposed a scale named GPIC (Global Information Privacy Concern) to measure consumer privacy. Malhotra et al, 2004 proposed a model to measure consumers’ information privacy concerns in an online scenario (IUIPC). Based on all these studies, we propose a list of factors which consumers have deemed important to their privacy, as follows:

**Collection:** This refers to whether the consumers are aware that information about them is being collected. For example, firms explicitly collect preference and personal information during initial registration.
or purchase. Firms also gather information about consumers passively through cookies and the consumers might not be aware that information about her is being collected. Finally, firms collect information about consumers by purchasing information from other firms or third party databases. Malhotra et al (2004), Sheehan and Hoy (2000) and Novak and Phelps (1997) suggest that the manner in which information is collected impacts consumers’ privacy concerns.

Unauthorized Secondary Use: Even if consumers provide information voluntarily during an initial transaction, they are still concerned about how the information will be used subsequently. An important component of information privacy is control (Malhotra et al, 2004). Firms can use consumer information in several ways: to send advertisements, to offer personalized products or services, rent or sell consumer information. Consumers prefer to have control over how the firm uses their information subsequently.

Fair Exchange: While consumers are not always averse to firms’ using information about them, they expect something of ‘value’ in return, such as more personalized offers or services. Milne and Gordon (1993) term this as the ‘second exchange’ and suggested that consumers are willing to give up some amount of privacy in exchange for a better product or service.

Type of Information: Consumers consider some types of information (such as personal information) more sensitive than other types (such as product preference information) – Sheehan & Hoy (2000).

Familiarity & Trust: Familiarity and trust are other factors which consumers consider important. Consumers’ privacy concerns are mitigated if the consumer is familiar with that entity (Wang et al, 1993).

Based on prior literature, we propose a conceptual model of how consumers respond to firms’ use of personal information as shown in Figure 1a below. The dependent variable is consumer response. The independent variable is firms’ use of consumer information. On one hand, use of consumer information enables advertisers to serve a personalized message. Research in computer science and marketing has shown that personalization leads to a better response from consumers. On the other hand, use of consumer information by a firm for personalization might also be perceived as a privacy violation by consumers. The extent of privacy violation perceived by the customer is mediated by the privacy factors mentioned above.
3. Data

One of the strengths of this research is the unique dataset that we gathered, which we shall describe in detail in this section. We collected data for this research from a web-based firm which acts as a distributor for a variety of products including long distance phone services, cellular plans, electricity, gas, health insurance, internet connections and mortgage lending. An advantage of data from such a diverse product set is that the disutility due to information overload is more prominent and hence the potential benefit due to personalization is larger than for a single product firm. The firm wishes to remain anonymous as a pre-condition for sharing this data with us, so we refer to it as A.

Firm A mainly relies on email advertisements to inform its customers about its products as well as to announce any new offers. It sent more than 10,000,000 emails to its customers over a nine month period from April – December 2002 (for the sake of analytical tractability, we select around 33,000 customers at random for our analysis; these customers received around 600,000 emails). For each email advertisement it sent out, firm A kept a record of what product was featured in the advertisement, who received the email and what action the user took after receiving the email. E.g., the firm kept track of whether the user opened the email or not (the firm can track whether the user opened an email by attaching an active link in the message body). If the user opened an email, the firm can also record if the user took any one of the following actions:

Figure 1a Conceptual Model Governing Consumer Response to Use of Information for Personalization
unsubscribed (she can click the unsubscribe link at the bottom of the email); no-action, made a click-through (but not a purchase) or made a purchase.

Firm A started operations in 1999 and by the time of our study, it had a user base of more than 590,000 customers – both ‘acquired’ and ‘organic’; an ‘organic’ customer is one who registers with the firm; an ‘acquired’ customer is one whose information was purchased by the firm from outside. About 60% of the customers are acquired; i.e., these customers visited the firms’ website and voluntarily provided information about themselves during registration. The rest 40% customers are acquired, i.e., information about these customers was purchased by firm A in early March 2002 when it acquired a database marketing firm. Firm A sent an initial email to all such customers announcing the acquisition and also mentioned that it would be sending regular emails to these customers in future. As is the commonly accepted practice, it offered customers an option to unsubscribe and stop receiving emails from firm A in the future.

Apart from the personal information gathered during registration, firm A also kept track of consumer preferences by grouping customers into pools. E.g., if a customer viewed an offer about natural gas at some point, she was placed in the ‘natural gas pool.’ A customer can also belong to more than one pool if she viewed offers in more than one product category. In the data, there is a large range of number of pools to which individual customers belong; we have customers who are not in any pool as well as customers who expressed interest in 19 different product categories. The mean number of product categories per customer is 1.95

Firm A uses this consumer information to personalize its email advertisements in two ways: one, it may greet customers by name in an email, such as ‘Dear Ms X’ or ‘Dear Mr Y’. This method is intrusive, because customers become aware that the firm was using information gathered in the past for a commercial purpose (i.e. advertising). Two, it may send emails to a customer about a product if that customer had shown an interest in the product in the past. E.g., in one email campaign, it sent an offer about long distance phone plans to customers in the ‘Long Distance’ pool. Sometimes, the firm sends an email advertisement to all customers in its database. E.g., if it sends an offer about satellite TV to all customers, then we consider the email personalized for customers in the ‘Satellite TV’ pool and non-personalized for the rest of the customers.
This method is non-intrusive, since the customer might not be aware that the firm is making an effort to offer a personalized advertisement. An email can have multiple levels of personalization if it contains both product based personalization and personalized greetings. A large majority of emails in our data do not contain any level of personalization. Appendix 1 shows a sample email which contains a personalized greeting, and also some descriptive statistics.

This data is especially suited for our study due to the following reasons: one, the setting in which the data was collected resembles a natural or quasi experiment in which the firm sent a mix of personalized and non-personalized emails at random to its consumers. Two, the response is measured at multiple levels using both non-financial (opening, click-through and unsubscription) and financial (purchases) measures.

4. Hypothesis

We formulate our hypothesis based on the conceptual model proposed in Figure 1a. As mentioned earlier, firm A uses two types of information (viz., name and product preference) about consumers in an effort to personalize the emails. According to the conceptual model in Figure 1a, use of this information for personalization can lead to both a positive effect (more relevant message) and a negative effect (due to privacy implications). Before we consider the privacy implications of using this information, we take a look at the privacy policy of firm A. In its privacy policy, firm A clearly mentions that the information collected will be used for sending email advertisements. It also specifies the firm’s policy on sharing this information with other third parties. In other words, the firm makes an effort to be transparent in its use of secondary information. Therefore, the question that arises is whether customers still feel a loss of privacy when they receive a personalized email from the firm. To address this question, we look at each type of information separately:

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12 The management at the firm informed us that they did not follow any well defined email advertisement strategy. They either sent an advertisement to all customers or to customers in a specific pool. E.g. they sent an email about phone cards to customers in the ‘phone card’ pool. Sometimes, they sent an email about phone cards to all customers in the ‘natural gas’ pool. Or they sent an email about phone cards to all their customers who are not in any pool or to all customers in their entire database. The firms did not conduct any indepth analysis of customer response to formulate future email advertisement strategies. In fact, one of the reasons this firm shared the data with us was that they had collected this vast amount of data on consumer responses to various types of emails and did not have the tools to analyze the same. The only clear direction that emerged from our discussions with the firm was that they made an effort to restrict the number of emails that a customer received in a given month to five or less.
**Product Preference Information:** Researchers in computer science and human-computer interaction have conducted experiments in controlled settings and reported that personalization based on targeted product recommendations leads to higher response rates than lack of personalization. For example, such experiments were conducted with subjects downloading online music (Tam et al, 2003), viewing online news (Lai et al, 2003) and locating items using search engines (Pitkow et al, 2002). Ansari and Mela (2003) find that customizing the links within an email can potentially improve click-through rate by 62%.

In light of our conceptual model in Figure 1a, the use of product preference information is expected to give a higher utility to consumers because they have to spend less time reading messages of no interest to them. On the other hand, consumers in our study might not notice that the firm is using product based personalization because the firm does not mention the same in the email (see Appendix 1 for sample email). Therefore, we expect that privacy concerns with this type of information use would be minimal in our analysis. Therefore, the first hypothesis we propose is as follows:

**Hypothesis 1:** A customer responds more positively to an advertisement if the email is personalized on the basis of her past interests.

**Personalized Greetings:** An important part of treating each customer individually is addressing the customer by name. Dale Carnegie once said that a person’s name is the sweetest sound in any language (Carnegie, 1936). Howard et al (1995) were the first study to test experimentally that individuals are more willing to comply with a request if the person making the request remembers and correctly mentions their name. They borrow from two theories in psychology literature – “the self serving bias” (Myers, 1987) and “the reciprocal positive regard” (Curtis and Miller, 1986). The theory of self serving bias suggests that people tend to make self-serving attributions to a variety of occurrences; therefore, the fact that someone remembers their name gives people a feeling of self-importance. According to the reciprocal positive regard theory, perception of another’s positive regard can produce reciprocal positive feelings; people consider it a compliment when someone remembers and correctly mentions their name and therefore more likely to comply with the rememberer’s request. For a detailed literature review, please refer to Howard et al (1995). Literature on sales has shown that using customers’ names in sales situations leads to improved sales (e.g.,
Levy et. al., 1992). Overall, a case can be made that greeting customers by name in offline scenarios leads to a positive response.

However, the dynamics of consumers’ reaction to personalized greetings could be different for online scenarios. It is unlikely that a customer would get a feeling of self-importance if a machine remembers her name and uses the same in an advertisement. So far, the use of name for personalization in online advertisements has not been studied. When a person sees her name in an advertisement, she may ask the following questions: one, where did the firm get my name? Two, does the firm have permission to use my name in email advertisements? Three, how interested am I in the message? A concept which is tied closely to use of personalized greetings in email advertisements is anonymity. A survey by Georgia Tech suggests that consumers value anonymity online. Use of a customer’s name in an email advertisement compromises the anonymity of the customer and might lead to a negative response. However, anonymity is closely tied to privacy because customers deem anonymity as an important step in protecting their privacy.13 We also examine the use of personalized greetings in light of the conceptual model in Figure 1a. Figure 1a also lists five factors which determine the extent of privacy violation experienced by customers.

**Collection:** The data used in our study was collected from two types of customers: organic - who voluntarily provided information to the firm, and acquired - who did not provide information voluntarily to this firm. Therefore, the latter group of customers is more likely to perceive a privacy violation after seeing their name in an email advertisement.

**Unauthorized Secondary Use:** Firm A has posted its privacy policy on its website which details how the firm will collect and use information about its customers. The acquired customers were sent an email explaining the acquisition of their information and were given an option to opt out of receiving future emails.

**Fair Exchange:** Use of a customer’s name conveys a sense of familiarity and customers expect a personalized message to follow a personalized greeting. However, if the name is followed by an advertisement about a product that the customer has no interest in, consumers may respond negatively

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because the firm is not giving them something of value (such as a targeted recommendation) in return for using their information.

**Type of Information:** Customers consider personal information (such as name) to be more sensitive than non-personal information (such as product preference information).

**Familiarity / Trust:** It is likely that consumers who are more familiar with a firm are less likely to respond negatively on seeing their name in an email advertisement.

Based on the above discussion, we propose the following hypotheses related to firms’ use of personalized greetings:

**Hypothesis 2:** Email advertisements which contain a personalized greeting without a targeted product recommendation are likely to lead to a negative response from customers.

**Hypothesis 3:** Email advertisements which contain a personalized greeting with a targeted product recommendation are likely to lead to a positive response from consumers.

**Hypothesis 4:** ‘Acquired’ customers react more negatively to personalized greetings than organic customers.

**Hypothesis 5:** Consumers who are familiar with a firm react less negatively to personalized greetings.

In our data, privacy is a latent construct and cannot be explicitly measured. However, the effects of privacy concerns are manifest in the observed consumer response. Therefore, we consider the observed response as our dependent variable. Based on our discussion in this section, the actual model that we test (Figure 1b) is a modified version of the conceptual model in Figure 1a. In addition, we also include consumer and promotion characteristics as control variables in our model (see details on next page).
Figure 1b: Model governing response to use of consumer information in email advertisements.

In our model, a consumer faces decisions at two levels – one, when she receives an email, she makes a decision whether or not to open it; two, if she opens the email, she can take any one of the following actions – unsubscribe, take no action, make a click through (without making a purchase) or make a purchase\(^\text{14}\). This can be represented in Figure 1c.

In the first stage of decision making, customers can see only the subject of the email but not the content. The subject contains the product which is advertised in the email. E.g., a typical subject line reads as “Protect your computer with Norton AntiVirus at an unbelievable price”. Therefore only product-based personalization is likely to affect the consumer response. Based on our discussion, we expect that product based personalization is likely to have a positive and significant impact on the customer’s probability of opening an email. Moreover, the privacy concerns in this type of personalization are minimal since the customer might not even be aware that the email is personalized. Response at this level is measured by whether the consumer opens the email or not. Personalized greetings do not play a role in determining consumer response at this stage because the consumer does not know whether the email contains a personalized greeting before she opens the email.

\(^{14}\) A customer can make a purchase with or without making a click-through on the email. E.g. she can visit the website on her own at a later date and make a purchase. Out of 231 different purchases in our sample, 128 were made by customers without making a click-through on the email.
Figure 2a summarizes the hypothesis in the first decision phase, i.e., when the customer decides whether or not to open an email. In addition to the factors mentioned above, we also include a variable measuring the frequency of emails sent by the firm to the customer. Prior literature in advertising postulates that the chances of a customer noticing an advertisement are directly proportional to the number of times the customer is exposed to an advertisement (Grossman and Shapiro, 1984). Berlyne (1970) suggests that the advertisement response function follows an inverted U-shape with increase in advertising frequency.

The second part of the decision making occurs after the customer has opened the email. At this stage, consumers have opened the email and become aware of whether the email greets them by name. Response at this stage is measured in four levels: one, whether the consumer unsubscribes; two, whether the consumer takes no action after opening (read the email); three, make a click-through (but not a purchase); and four, make a purchase. Since these response can be ranked in an ordinal manner with ‘unsubscribe’ being the least desirable action and ‘purchase’ being the most desirable action, a positive effect of personalization would mean shifting the consumers’ propensity from unsubscribe to no-action to click-through to purchase.

Figure 2b summarizes the factors which influence consumer decision in the second stage, i.e., how a consumer responds after she has opened the email. Prior studies on the effectiveness of advertisements in marketing literature have determined that consumer response to advertisements depends on the characteristics of the advertisement (Walters et al 1986). Therefore, we use promotion characteristics as control variables. We measure the characteristics of the advertisement in three ways: one, whether the
advertisement mentioned the product price or not; two, whether the email offered a free gift or a discount; and three, whether the email offered a comparison with competitors’ prices. 

5. Estimation Model

In our model, we let consumers be heterogeneous in their response rates as well as in their preference for personalization and privacy. E.g., prior literature shows that privacy concerns depend on individual attitudes and demographic variables (Culnan 1993, Wang and Petrison 1993). Moe et al (2003) suggest that different consumers follow different browsing patterns and the rate at which a customer returns to an online store depends on a latent rate inherent to that individual. We propose a model which is flexible enough to incorporate both observable and unobservable consumer specific heterogeneity in our parameter estimates. Several researchers have addressed the issue of specifying and measuring the heterogeneity among consumers using different techniques such as random intercepts (Chintagunta et al 1991) or random parameters (Gonul & Srinivasan 1993). Any model which ignores this heterogeneity among consumers could lead to biased and inconsistent estimates of the marketing variables (Hsiao, 1986).

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15 The controls that we use for email characteristics (e-mails involve discount offers, comparisons with competitors, etc) are applicable to both personalized as well as non-personalized emails. In other words, personalization and these controls are not mutually exclusive. E.g. there may be personalized emails which feature discount offers, other personalized emails may feature comparison with competitors, and so on. Similarly, there may be non-personalized emails which feature discount offers and so on.
We account for consumer heterogeneity by estimating individual level parameters, which are viewed as draws from a super population distribution often referred to as the mixing distribution. There are two common ways to represent consumer heterogeneity in choice models – continuous & discrete heterogeneity, depending on the nature of the mixing distribution. With continuous heterogeneity, the mixing distribution is continuous (e.g., normal) and individual specific parameters are drawn from this distribution. Monte Carlo Markov Chain (MCMC) methods are commonly used to estimate the exact posterior distribution of individual specific parameters (e.g. Rossi et al, 1996). With discrete heterogeneity, the mixing distribution is discrete with mass points (which correspond to consumer segments) and a finite mixture model (e.g., Kamakura & Russell, 1989) is used to estimate segment specific parameters. We should clarify at this stage that even though we have two stages in consumer decision making, they need not be estimate jointly. Stage 2 is conditional on stage 1, therefore, we can simply multiply the estimates from stage 2 with the probability of opening email (stage 1) to get joint probabilities.

5.1 Stage 1

The utility assigned to consumer $n$ for email $j$ can be specified as:

$$U_{jn} = \theta_n \cdot X_{jn} + \varepsilon_{jn}$$  \hspace{1cm} (1)

for $j = 1,2,...J_n$ and $n=1,2,...N$ where $J_n$ is the total number of emails received by consumer $n$, $N$ is the total number of consumers and $\theta_n$ are the individual specific parameters (which also include an intercept) to be estimated. An individual specific parameter estimate means that our model would allow us to estimate the impact of $X$ (our variables of interest) for each individual separately. This is unlike pooled regression where we estimate the average impact across all consumers. The observable dependent variable $y$ can take two discrete values (‘0’ if the consumer does not open the email; and ‘1’ if the consumer opens the email) depending on the value of the latent variable $U_{jn}$. Specifically, $y_{jn} = 0$ if $U_{jn} < 0$ and $y_{jn} = 1$ otherwise. We assume that the stochastic component $\varepsilon_{jn}$ is distributed normally with a mean 0 and variance equal to 1. Thus the probability that customer $n$ selects choice $i$ for email $j$ is given by a standard probit model as:

$$P_i(U_{jn}, \theta_n, X_{jn}) = \left[1 - \Phi(\theta_n \cdot X_{jn})\right]^{y_{jn}} \cdot \left[\Phi(\theta_n \cdot X_{jn})\right]^{1-y_{jn}}$$  \hspace{1cm} (2)

The independent variables $X$ of interest in our model are:
• **PRODUCT**: Whether email features only product based personalization. This variable is 0 if the email is not personalized and 1 otherwise.

• **OPEN\(_{t-1}\)**: whether the customer opened the prior email that she received. \(OPEN_{t-1}\) is 1 if the customer opened the prior email and ‘0’ otherwise.

To control for the frequency of emails, we use a variable **FREQUENCY** which indicates the number of emails received by the customer in the last 30 days from this firm. Since existing theory predicts a U-shaped response curve to frequency of emails, we also incorporate another variable **FREQUENCY\_SQR**, which is the square of the **FREQUENCY** variable.

We further specify each individual specific parameter \(\theta_n\) to be drawn from a continuous normal distribution (Rossi et al 1996). This provides a flexible random component specification which allows us to incorporate both observable and unobservable consumer specific heterogeneity. We specify the multivariate regression

\[
\theta_n = \Psi Z_n + \mu_n \quad \text{and} \quad \mu_n \sim i.i.d. \, N(0, V_\mu)
\]  

(3)

where the individual specific coefficients \(\theta_n\) are regressed on the observable consumer characteristics \(Z_n\) (including an intercept), \(\mu_n\) is the unobservable component of the consumer heterogeneity and \(V_\mu\) is the variance-covariance matrix whose diagonal elements represent what fraction of the variance of \(\theta\) is unexplained by observable consumer characteristics. Recall that \(\theta_n\) captures the impact of \(X\) on probability of opening an email. Equation (3) argues that these parameters themselves are affected by observable and unobserved consumer heterogeneity. We have information about two observable customer characteristics – one, whether the customer is *acquired* or *organic* and two, whether the customer made any prior purchases. Therefore, we define two variables

• **ACQUIRED**: If information about the customer is acquired from outside. **ACQUIRED**=0 (1) if the customer is *organic* (*acquired*).

• **PURCHASE**: Whether the customer made any purchase prior to the commencement of our study.

**PURCHASE** =1 (0) if the customer made (did not make) a purchase.
For inference, we use a hierarchical Bayesian model. For a discussion on the priors and conditional posteriors of this model, please refer to the Technical Appendix A1. The advantages of using the Bayesian analysis as compared to standard econometric analysis are as follows: one, some customers have sparse observations. E.g., about a ¼th of the customers received only one email; therefore we have only one data points about these customers. Classical techniques which rely on the asymptotic properties of large samples may give biased estimates. Two, since we estimate a large number of parameters (33196 customers and 5 parameters each), maximizing the likelihood function using classical estimation methods which rely on closed form solutions can be very cumbersome.

5.2 Stage 2

In the second stage, the customer makes a decision after opening the email in the first stage. She can take any one of the following actions – 1, if she unsubscribes from the mailing list by clicking on the unsubscribe link at the bottom of the email; 2, if she only opens the email and takes no action; 3, if she clicks through to visit the firms’ website (but does not make a purchase); and 4, if she purchases the product featured in the offer. Since there is a clear ordinal ranking among these responses depending on consumer utility (e.g. at worst, the customer unsubscribes from the mailing list and at best, she makes a purchase), we can use an ordered probit model (Greene, 2003). In the second stage, both product-based personalization as well as personalized greetings are likely to influence consumer choice. Therefore, we use three independent variables to represent personalization. \( PRODUCT \) represents the case when the email only features the consumers’ product of interest; \( NAME \) for the case when the email contains only a personalized greeting; and \( BOTH \) when the email contains both levels of personalization. Our baseline case is when none of the elements of personalization is present in the email. The variables that we use to characterize personalization are given in Table 1. E.g., if the advertisement has product based personalization as well as a personalized greeting, then \( BOTH = 1 \) and \( PRODUCT = NAME = 0 \) and so on.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Based on Consumer Past Interests</th>
<th>Based on Personalized Greeting</th>
</tr>
</thead>
<tbody>
<tr>
<td>( PRODUCT (=1) )</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>( NAME (=1) )</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>( BOTH (=1) )</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Table 1: Multiple Levels of Personalization
In an ordered probit model, the latent utility function is specified as:

$$U_{km} = \beta_m \cdot W_{km} + \xi_{km}$$  \hspace{2cm} (4)$$

where $k = 1,2,...K_m$ is the number of emails opened by consumer $m$ and $m = 1...M$ is the number of consumers who opened at least one email. $\beta_m$ are the individual level parameters to be estimated and $W$ are the independent variables. The consumer utility in the second stage is conditional on opening the email in the first stage.\footnote{The $U_{km}$ term should actually be written as $U_{km|o}$ to indicate that the utility is conditional on the customer opening the email in the first stage. For the sake of notational convenience, we drop the ‘$|o$’ subscript.} In an ordered probit model, consumer $m$ chooses choice $h$ if $\alpha_{m,h-1} < U_{km} < \alpha_{m,h}$ where $\alpha$ are the cutoff points that are estimated along with $\beta$’s. Since $\xi$ is distributed normal, probability of observing choice $h$ is given as $P_h(U_{km}, \beta_m \cdot W_{km}) = \Phi(\alpha_{m,h} - \beta_m \cdot W_{km}) - \Phi(\alpha_{(h-1)m} - \beta_m \cdot W_{km})$.

Since consumer in our sample have four choices, we use $\alpha_{0m} = -\infty$ and $\alpha_{4m} = \infty$ restriction for purposes of identification (i.e. the lower and upper bounds on the cut-off points), as is common in literature. The parameters to be estimated include the coefficients $\beta_m$ and the three cutoff points of the ordered probit model. We define $\delta_m = [\alpha_m, \beta_m]$ as the set of individual level parameters to be estimated, where $h = 1,2,3$. Again note that the vector of parameters $\delta_m$ is estimated for each consumer separately. Here, we jointly estimate the cutoff points and coefficients using a form of the Gibbs sampler known as the ‘collapsed Gibbs’ sampler (Liu et al, 1994). Cowles (1996) shows that such a model is more efficient than a pure Gibbs sampler based method of estimating an ordered probit model as specified by Albert & Chib (1993). The independent variables of interest $W$ relevant at this stage include the three personalization variables PRODUCT, NAME and BOTH in Table 1 as well as other independent variables such as:

- **RESPONSE\textsubscript{t-1}**: whether the customer made a click-through or purchase on the prior email that she opened. **RESPONSE\textsubscript{t-1}** is ‘1’ if the customer made a click-through or purchase on the prior email.
- **PRICE**: Whether the email mentions the price offer or not. **PRICE** is ‘1’ if the email mentions price and 0 otherwise.
- **GIFT**: Whether the advertisement offered a free gift, price off or cash back with the purchase.
- **COMPARISON**: Whether the advertisement contained price comparison with competitors.
Similar to the hierarchical Bayesian model in Section 4.1, we specify each individual specific parameter $\delta_m$ to be drawn from a continuous normal distribution.

$$\delta_m = \Delta \cdot Z_m + \nu_m \text{ and } \nu_m \sim iid.N(0,V_{\delta})$$ (5)

where $Z_m$ are the observable customer specific variables, including an intercept term. As in stage 1, we include two customer specific variables: one, whether the customer is acquired (ACQUIRED) and two, whether the customer made a purchase in the past (PURCHASE).

6. Results
6.1 Stage 1 – before opening an email advertisement

We run the MCMC simulation for 12000 draws and discard the first 6000 as burn-in. Further, we use a thinning parameter of 4, i.e. out of the remaining 6000 draws, we retain every fourth draw for our posterior distribution. The mean of the rejection rate for the Metropolis-Hasting (M-H) algorithm is 0.79 which is within the desired rejection rate of 0.6-0.9. The mean log-likelihood is -59129.4. We conducted two tests to check for the convergence of our MCMC output – the Heidelberg (Heidelberger and Welch, 1983) and the Geweke (Geweke, 1992) diagnostic tests. Both tests indicate adequate convergence. Table 2 summarizes the posterior distribution of the individual specific means of the parameters ($\theta_n$) in eq (1).

<table>
<thead>
<tr>
<th>$\theta_n$</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>probability greater than zero</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-2.85***</td>
<td>0.75</td>
<td>0.00</td>
</tr>
<tr>
<td>$\theta_{PRODUCT}$</td>
<td>0.22***</td>
<td>0.1</td>
<td>0.99</td>
</tr>
<tr>
<td>$\theta_{OPEN-I}$</td>
<td>0.8***</td>
<td>0.23</td>
<td>0.99</td>
</tr>
<tr>
<td>$\theta_{FREQUENCY}$</td>
<td>0.04</td>
<td>0.22</td>
<td>0.62</td>
</tr>
<tr>
<td>$\theta_{FREQUENCY_SQR}$</td>
<td>-0.11**</td>
<td>0.04</td>
<td>0.03</td>
</tr>
</tbody>
</table>

Table 2: Posterior Distribution of $\theta_n$

The mean values are collected by averaging the mean values for estimated parameter for each consumer. * (**) denotes that more than 90% of the values in the posterior distribution are positive (negative). This is equivalent to a one tailed significance test at p<0.1 level in classical regression. Similarly ++, +++ (or **, ***) are equivalent to significance at the p<0.05 and p<0.01 level respectively. We continue with this notation for the rest of the paper. Table 2 can be interpreted as follows: Consider the row $\theta_{PRODUCT}$. The value 0.22 suggests that the mean of the posterior distribution of individual specific coefficients for the product-based...
personalization variable 0.22 and the standard deviation is 0.1. The third column (probability greater than zero) suggests that 99% of customers have a positive mean for the \( \theta_{\text{PRODUCT}} \); which suggests that more than 99% customers respond positively to emails which contain product based personalization. Thus hypothesis \( H1 \) is supported.

To understand the how \( \theta_{\text{PRODUCT}} \) varies across consumers, we plot posterior distribution of individual specific means of \( \theta_{\text{PRODUCT}} \) (i.e. we plot the mean value of \( \theta_{\text{PRODUCT}} \) for each consumer) in Figure 3. While it is positive for more than 99% of consumers, the bimodal shape is interesting. It seems that one segment of population is clustered around the 0.15 and the other one is clustered around 0.33. Clearly, the latter segment is highly responsive to product based personalization in their propensity to open an email. This is also a key advantage of our method which allows us to estimate the parameters at individual level. We can measure the response at a very micro level which can be used by managers to target each individual.

![Distribution of Individual Specific Means for \( \theta_{\text{PRODUCT}} \)](image)

**Figure 3: Distribution of Individual Specific Means for \( \theta_{\text{PRODUCT}} \)**

Next, we present the result of estimates of eq (3). In eq (3), we let \( \theta \) (estimated in table 2) itself be regressed against some observed individual characteristic namely, whether the consumer was acquired and whether consumer had purchased previously. Thus, table 3 presents the means and standard deviation (in brackets) of the posterior distribution of the hierarchical regression coefficients \( \psi \).

<table>
<thead>
<tr>
<th>( \theta )</th>
<th>Intercept</th>
<th>ACQUIRED</th>
<th>PURCHASE</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Constant</strong></td>
<td>-2.90 (0.034)***</td>
<td>0.14 (0.028)***</td>
<td>0.19 (0.05)***</td>
</tr>
<tr>
<td>( \theta_{\text{PRODUCT}} )</td>
<td>0.13 (0.071)***</td>
<td>0.19 (0.0073)***</td>
<td>-0.013 (0.03)</td>
</tr>
<tr>
<td>( \theta_{\text{OPEN}-1} )</td>
<td>0.81 (0.03)***</td>
<td>-0.01 (0.03)</td>
<td>-0.17 (0.03)***</td>
</tr>
<tr>
<td>( \theta_{\text{FREQUENCY}} )</td>
<td>0.11 (0.026)***</td>
<td>-0.20 (0.02)***</td>
<td>0.23 (0.03)***</td>
</tr>
</tbody>
</table>
Each row in Table 3 gives the coefficient of the observable consumer variable $Z_n$ on the model parameters $\theta$. E.g. $\theta_{PRODUCT}$ has an intercept of 0.13 (second row). This implies that customers who are not acquired and have not made any past purchase ($ACQUIRED = 0$, $PURCHASE = 0$), on average, have a $\theta_{PRODUCT}$ of 0.13 and so on. Similarly, acquired customers have a positive coefficient for $\theta_{PRODUCT}$ (=0.19) suggesting that targeting emails based on preferences works better for acquired customers than for organic customers, given that all other parameters are the same. The negative coefficient of $ACQUIRED$ for the $\theta_{FREQUENCY}$ (= -0.20) variable suggests that acquired customers respond less positively to an increase in frequency of emails than organic customers. The coefficient of the $PURCHASE$ variable for the constant term is positive and significant suggesting that customers who made a purchase in the past are more likely to open an email; thus hypothesis H5 is supported. The coefficient of $ACQUIRED$ for the constant term is positive and significant, suggesting that acquired customers are more likely to open emails than organic customers; this contradicts hypothesis H4.

6.1.1 Discussion of Stage 1 Results

The analysis of Stage 1 shows some interesting results on how different types of customers respond to email advertisements. One, acquired customers are more likely to open an email than organic customers. The intuition for this is that organic customers, on average, have been with the firm for much longer prior to our study. Therefore, these customers are in a better position to decide whether an email is of interest to them just by looking at the subject and are more discerning in opening emails. This reasoning is further validated in the second stage where we find that organic customers are more likely to buy/make a click through than acquired customers. Another possible reason for this could be that acquired customers are curious to know about this firm’s products and services and are hence more likely to open an email. This result that acquired customers are more likely to open an email has implications for firms (such as spammers) whose revenue is primarily based on the fraction of emails that are opened.

Two, customers are more likely to open an email if the email features a product of interest for the consumer. Acquired customers respond more positively to product based personalization. While this result looks
surprising, the intuition is similar to above; i.e., acquired customers are more likely to open an email than organic customers. Therefore, product based personalization leads to a greater increase for acquired than organic customers. In real life too, we observe that spammers constantly cultivate new email addresses because users are more likely to click on an email advertisement from an unknown firm that a known one.

Third, firms can also tailor the frequency of emails to different customers. E.g., organic customers prefer to receive more emails than acquired customers. Similarly, customers who made prior purchases with the firm have a higher threshold than those who did not make prior purchases.

6.2 Stage 2 – after opening an email advertisement

In the second stage, we run the MCMC simulation for 27000 draws and discard the first 20000 as burn-in. Further, we use a thinning parameter of 5, i.e. out of the remaining 7000 draws, we retain every fifth draw. The mean of the rejection rate for the M-H algorithm is 0.84. The mean log-likelihood is -6874.2. Both the Heidelberg (Heidelberger and Welch, 1983) and the Geweke (Geweke, 1992) diagnostic tests indicate adequate convergence. Again, we first present the estimates from the ordered probit. Table 4 summarizes the posterior distribution of the individual specific means of the model parameters ($\beta_m$) in equation (4) and the individual specific cutoff points ($\alpha_1^m$, $\alpha_2^m$, $\alpha_3^m$) of the ordered probit model.

<table>
<thead>
<tr>
<th>$\delta_m$</th>
<th>Mean</th>
<th>S.D.</th>
<th>probability greater than zero</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_1$</td>
<td>-3.66*</td>
<td>1.61</td>
<td>0.08</td>
</tr>
<tr>
<td>$\alpha_2$</td>
<td>2.56***</td>
<td>0.66</td>
<td>1.0</td>
</tr>
<tr>
<td>$\alpha_3$</td>
<td>3.75***</td>
<td>1.02</td>
<td>0.99</td>
</tr>
<tr>
<td>$\theta_{PRICE}$</td>
<td>0.08</td>
<td>0.22</td>
<td>0.69</td>
</tr>
<tr>
<td>$\theta_{COMPARISON}$</td>
<td>-0.5***</td>
<td>0.19</td>
<td>0.01</td>
</tr>
<tr>
<td>$\theta_{GIFT}$</td>
<td>-0.15</td>
<td>0.15</td>
<td>0.12</td>
</tr>
<tr>
<td>$\theta_{RESPONSE \text{-1}}$</td>
<td>0.22</td>
<td>0.35</td>
<td>0.65</td>
</tr>
<tr>
<td>$\theta_{PRODUCT}$</td>
<td>0.48**</td>
<td>0.24</td>
<td>0.98</td>
</tr>
<tr>
<td>$\theta_{NAME}$</td>
<td>-0.27</td>
<td>0.18</td>
<td>0.07</td>
</tr>
<tr>
<td>$\theta_{BOTH}$</td>
<td>0.15</td>
<td>0.32</td>
<td>0.67</td>
</tr>
</tbody>
</table>

Table 4: Posterior Distribution of $\delta_m$

The key variables of interest are the personalization variables. Note that while response to product based personalization is highly positive (for 98% of consumers), response to name based personalization is highly negative (for 93% of consumers). When a consumer receives an email with both product and name based personalization, its impact is moderately positive.
To understand the difference in consumer response to different types of personalization, we plot the posterior means of the individual level coefficients of the personalization variables in Figure 4. E.g. Figure 4a shows that almost all customers have a positive posterior mean for $\delta_{PRODUCT}$, suggesting that customers prefer to receive emails with product based personalization; thus hypothesis $H1$ is supported. Thus product based personalization leads to an increase in click-through and purchase probabilities as well as a decrease in unsubscriptions. This plot also suggests that there are two segments of consumers.

Similarly, Figure 4b represents the density of the individual specific posterior means of $\delta_{NAME}$. From our MCMC output, we see that more than 90% customers have a negative mean vale for $\delta_{NAME}$; showing that hypothesis $H2$ is supported. This result is interesting because it suggests that consumers’ attitude towards personalized greeting in email advertisements differs from that in offline sales situations where personalized greetings are associated with higher sales. This is surprising considering that most customers themselves registered with the firm and provided their name and other information in our database. We find that sending an email with only a personalized greeting, without targeted product recommendations, can result in a negative response from consumers. One possible explanation is that greeting a consumer by name compromises the anonymity of the consumer, which can raises a privacy flag; so the customer might not be
inclined to click on the link. E.g. a survey by Georgia Tech reported that users value being able to visit sites on the Internet in an anonymous manner\(^ {18} \). Another possible reason is that greeting a customer by name signals that the firm knows the customer well; therefore when a customer sees her name in an email, she might expect a higher level of personalization such as a personalized offer or relevant recommendation\(^ {19} \). Thus, a customer may summarizes his reaction to personalized emails as follows “I already know that eBay knows my account ID and email address, and I don’t care. The fact that they can pull this information from a database and slap it into a bulk email doesn’t impress me in the slightest: the content of the email that they're sending to me is still totally generic, reflecting nothing about my interests or history with eBay.”\(^ {20} \) The fact that more than 62% of customers respond positively (Figure 4c) when a personalized greeting is followed by a targeted product recommendation further collaborates this conjecture that a majority of customers expect firms to provide them a personalized recommendation in exchange for using their name in an advertisement.

The above results show that consumers perceive different types of personalization differently. By definition, personalization based on targeted product recommendation is passive and non-intrusive (the consumer may not be aware that the firm is using personalization) and the consumer does not have to spend any cognitive effort to react to this type of personalization. On the other hand, personalized greetings are intrusive because the customer becomes aware that the firm is trying to offer her a personalized experience. This signals a privacy violation (Houston et al 1975) and can increase the cognitive effort that the customer spends when viewing the advertisement. In an experiment with customer service situations, Surprenant & Solomon (1987) show that some forms of personalization require increased cognitive effort from the consumer and result in reduced consumer satisfaction. Figure 4c shows the individual specific means for \( \delta_{BOTH} \); from this graph, it is clear that there are two segments of consumers, based on their response if an email is personalized at multiple levels. While one segment of customers reacts negatively to multiple levels of personalization, another segment reacts positively. Therefore, our results provide mixed support for hypothesis \( H3 \)

\(^{18}\) http://www.gvu.gatech.edu/user_surveys/survey-1998-10/ - 05/01/2005
This result is also surprising considering that continuous heterogeneity models generally rule out the existence of segments. E.g., Allenby and Ginter, 1995 suggest “segments are created because firms allocate resources differently (i.e. a decision of the firm), not necessarily because consumers are homogeneous”. Our results show that segments exist even when we assume continuous heterogeneity in distribution of consumer parameters and that we can classify consumers into finite groups based on their preference for personalization and privacy.

**Personalized Greetings and Privacy**

It can be argued that the negative response due to personalized greetings may not be due to privacy, but due to other unknown factors. One alternative explanation is that the database is incorrect because most customers supply false names while registering.\(^{21}\) While this is a valid argument, this does not explain the fact that more than 90% customers respond negatively to name. Moreover, this also does not explain why a segment of customers responds more positively to name when the email also contains a targeted recommendation. Another alternative explanation is that personalized greeting compromises customers’ anonymity and hence leads to negative response. Anonymity and privacy, however, can be looked at as two sides of the same coin because anonymity is one mechanism to protect privacy.

Finally, we also estimate equation (5) which outlines the relationship between estimated parameters and observable consumer characteristics. Table 5 provides the means and standard deviation (in brackets) of the posterior distribution of $\Delta$ of the multivariate regression specified in equation 5.

<table>
<thead>
<tr>
<th>$\delta$</th>
<th>Intercept</th>
<th>ACQUIRED</th>
<th>PURCHASE</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_1$</td>
<td>-3.40 (0.09)***</td>
<td>-0.15 (0.13)</td>
<td>-0.88 (0.14)***</td>
</tr>
<tr>
<td>$\alpha_2$</td>
<td>2.62 (0.06)***</td>
<td>0.20 (0.08)***</td>
<td>-0.66 (0.07)***</td>
</tr>
<tr>
<td>$\alpha_3$</td>
<td>3.55 (0.19)***</td>
<td>0.61 (0.32)**</td>
<td>-0.08 (0.22)</td>
</tr>
<tr>
<td>PRICE</td>
<td>0.08 (0.067)</td>
<td>0.09 (0.07)</td>
<td>-0.18 (0.08)***</td>
</tr>
<tr>
<td>COMPARISON</td>
<td>-0.40 (0.06)***</td>
<td>-0.19 (0.1)***</td>
<td>0.003 (0.11)</td>
</tr>
<tr>
<td>GIFT</td>
<td>-0.19 (0.06)***</td>
<td>0.15 (0.07)***</td>
<td>-0.06 (0.08)</td>
</tr>
<tr>
<td>RESPONSE(_{t-1})</td>
<td>0.43 (0.06)***</td>
<td>-0.47 (0.11)***</td>
<td>-0.22 (0.08)***</td>
</tr>
<tr>
<td>PRODUCT</td>
<td>0.66 (0.12)***</td>
<td>-0.33 (0.27)**</td>
<td>-0.30 (0.11)***</td>
</tr>
<tr>
<td>NAME</td>
<td>-0.24 (0.05)***</td>
<td>-0.005 (0.113)</td>
<td>-0.13 (0.1)</td>
</tr>
<tr>
<td>BOTH</td>
<td>0.32 (0.11)***</td>
<td>-0.40 (0.16)***</td>
<td>-0.07 (0.11)</td>
</tr>
</tbody>
</table>

Table 5: Posterior Distribution of $\Delta$

\(^{21}\) We would like to thank an anonymous reviewer for raising this important issue.
Some key results are as follows: One, the coefficients of the ACQUIRED variable are positive and significant for $\alpha_2$ and $\alpha_3$, suggesting that acquired customers are less likely to make a click-through or a purchase than customers who register with the firm on their own, if all other parameters are the same; this supports hypothesis $H5c$. This is highlighted in Figure 5.

![Figure 5: Impact of ACQUIRED variable on the ordered probit cutoff points](image)

The coefficients $\alpha_{i,n}$ (solid line) represent the cutoff points for the organic customers and the coefficients $\alpha_{i,a}$ (dashed line) represent the cutoff points for the acquired customers in the ordered probit model. From the figure, it is clear that acquired customers have a lower probability of making a click-through or a purchase than the organic customers because the cutoff points of the ordered probit model shift rightwards for acquired customers. Similarly, the coefficient of PURCHASES variable for $\alpha_1$ and $\alpha_2$ are negative and significant, suggesting that customers who purchased in the past are less likely to unsubscribe and more likely to make a click-through than customers who did not purchase in the past, supporting hypothesis $H5$.

### 6.2.1 Discussion of Stage 2 Results

Apart from highlighting consumers’ personalization and privacy concerns, the analysis in Stage 2 offers additional insights to predict consumer behavior after she opens an email advertisement.

**Collection: Acquired versus Organic Customers**

One, organic customers are more likely to make a click-through or purchase than acquired customers. This is contrary to Stage 1 where we find that organic customers are less likely to open email. We conjecture that organic customers are more discerning in opening email advertisements and only open emails where they are more interested in the product. We also find that there is no significant difference between organic and
acquired customers in their response to \textit{NAME} variable. However, the coefficient of \textit{ACQUIRED} variable is negative and significant for both $\delta_{\text{NAME}}$ and $\delta_{\text{BOTH}}$, suggesting that acquired customers are more privacy sensitive and always react negatively to personalized greetings, irrespective of whether the email contains a targeted recommendation, supporting hypothesis \textit{H4}.

\textbf{Familiarity: Whether customer made a prior purchase}

We also find that customers who made a prior purchase are more likely to respond positively after opening an email. This is similar to the result in Stage 1. However, we do not find any significant difference in consumer’s response to \textit{NAME} and \textit{BOTH} based on whether they made a prior purchase.

\textbf{6.3 Consumer Segments}

To understand how consumers differ in their response to different types of personalization, we perform a clustering analysis of the individual specific coefficients for \textit{PRODUCT}, \textit{NAME} and \textit{BOTH}. We use k-means clustering, which is a popular method for identifying segments of homogenous customers within a population. Our \textit{k-means} clustering suggests that there are 5 main segments of customers.\footnote{In \textit{k-means} clustering, we have to specify the number of segments ex-ante. In our analysis, we start with 2 segments and iteratively proceed till further analysis reveals very small segment sizes (with membership less than 2%).} These are as follows:

<table>
<thead>
<tr>
<th></th>
<th>\textit{PRODUCT}</th>
<th>\textit{NAME}</th>
<th>\textit{BOTH}</th>
<th>SIZE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>0.31</td>
<td>-0.37</td>
<td>0.4</td>
<td>13.6</td>
</tr>
<tr>
<td>B</td>
<td>0.29</td>
<td>-0.31</td>
<td>-0.01</td>
<td>31.8</td>
</tr>
<tr>
<td>C</td>
<td>0.68</td>
<td>-0.28</td>
<td>0.42</td>
<td>36.0</td>
</tr>
<tr>
<td>D</td>
<td>0.33</td>
<td>-0.07</td>
<td>-0.46</td>
<td>8.7</td>
</tr>
<tr>
<td>E</td>
<td>0.75</td>
<td>-0.07</td>
<td>-0.07</td>
<td>9.9</td>
</tr>
</tbody>
</table>

Table 6: Segment Parameters

The average characteristics of these segments in terms of their click-through, buying and unsubscripti on behavior are given in Table 7. E.g. customers in segment \textit{E} have a 23.4\% chance of unsubscribing, 63.7\% chance of taking no action, and a 12.7.6\% chance of making a click-through (without making a purchase). They have a 0.2\% probability of purchase.
Based on the response of these six groups to the personalization variables, we identify three broad levels of response: First, customers in segment A (about 13.6% of the sample) have a negative posterior mean of $\delta_{NAME}$ but a positive mean of $\delta_{BOTH}$. Moreover, the mean of $\delta_{BOTH}$ is greater than the mean of $\delta_{PRODUCT}$, suggesting that adding a personalized greeting adds more value than sending an email with only product-based personalization. We label these customers as ‘loyal’ consumers since they have the highest purchase rates of all segments (Table 7). This suggests that customers who are familiar with the firm, in terms of buying behavior, prefer to receive personalized greetings followed by targeted product recommendations (Louis and Westin 1997); in other words, familiarity mitigates privacy concerns. The unsubscription rate is the lowest for this segment. 3% of customers in this segment are acquired and the rest are organic.

Second, the posterior mean of $\delta_{BOTH}$ for segments B and C is either close to zero or is less positive than the mean of $\delta_{PRODUCT}$. This suggests that multiple levels of personalization mitigate the privacy concerns of these consumers; but overall, firms are better off sending only product based personalized emails to these customers. We label these customers as ‘moderate’ and these constitute around 67.8% of the market. Their unsubscription rates lie between those of the other two segments. About 40% customers in the ‘moderate’ segment are acquired and the rest are organic.

Finally, segments D and E always react negatively to personalized greetings, irrespective of whether the email contains a targeted product recommendation, i.e., the means of $\delta_{NAME}$ as well as $\delta_{BOTH}$ are negative for customers in these groups. We label these consumers as ‘privacy conscious’ because these customers always respond negatively if the firm uses personally identifiable information such as name in an email. This
segment comprises 28% of customers and has the highest unsubscription rate (see Table 7). 38% of customers in this segment are \textit{acquired} and the rest are \textit{organic}.

Based on these observations, for a firm seeking to implement an email based personalization solution, we recommend that the firm follow a \textit{targeted} personalization strategy as follows:

- For customers who make little or no purchases (\textbf{segments B & C}), the firm should send them email advertisements featuring only their product(s) of interest.
- For customers who have higher purchase rates (\textbf{segment A}), the firm should personalize both the message as well as the greeting.

Overall, we can show that such a targeted personalization scheme can lead to an increase in email advertisement profitability than the next best personalization scheme (i.e., sending only product personalized emails to all customers). To summarize, our results indicate that recommendations based on past preferences indeed result in an increased response rates for email advertising. However, personalized greetings alone lead to a decrease in response rates; suggesting that firms should not blindly follow the trend of greeting customers by name in email advertisements. Moreover, we observe that using multiple levels of personalization yields higher response rates for some customers, suggesting that some consumers are less privacy sensitive if personal information is accompanied with meaningful predictions about their preferences.

7. Conclusions & Extensions

To summarize, in this study, we observe how consumers respond to different types of information use by firms. We find that use of name in an email without a targeted product recommendation leads to a negative response from firms. Although there is sufficient theoretical background to suggest that this negative response is likely due to privacy concerns, the question that one can ask is whether the negative response due to use of name is entirely due to privacy or is it due to some other factor as well? While it is true that privacy may not be the only factor governing this relationship, there are other pieces of evidence from our study which strengthen this link. One, use of name in an email compromises the customer’s anonymity which in turn can lead to a privacy violation. Two, we find that a majority of customers respond positively when a personalized greeting is followed with a relevant recommendation. Three, we find that customers who
always respond negatively to personalized greetings have, on average, a higher probability of unsubscribing and the lowest probability of buying compared to all other customers. Four, customers who have the highest probability of buying also respond positively when personalized greeting is followed by a targeted recommendation. This suggests that familiarity with a firm is likely to mitigate the negative feelings associated with seeing ones’ name in an advertisement. Finally, we find that acquired customers always respond negatively to personalized greetings; acquired customers by nature are more privacy conscious than organic customers because the firm obtained details about them without their consent.

To our knowledge, this research is the first attempt to develop and test hypotheses related to the impact of personalization and privacy on the effectiveness of email advertisements using data from a real world setting. Our study provides support in favor of investing in personalization technologies and at the same time highlights the privacy concerns of consumers. On one hand, we show that emails personalized on the basis of past consumer behavior are more likely to generate a positive response from consumers. In any form of advertising, the effectiveness of the advertisement depends on getting the message across to the consumer. The higher opening rates and click-through rates for emails with product based personalization suggests that in an era of spam filters and discerning consumers (who ignore most email advertisements), product based personalized emails are an effective tool to reach audiences. Consumers are also less likely to unsubscribe if they receive a product based personalized email. On the other hand, we also show that a majority of consumers respond negatively if the firm greets them by name in an email advertisement. Thus, the practice of greeting all consumers by name in email advertisements, which is widely used by firms, may yield negative benefits for the firm. In other words, email marketers may be better off ignoring Dale Carnegie’s advice because ‘the sound of ones name might not be the sweetest thing to hear for a customer during an email advertisement’. However, consumers who buy more often from the firm respond positively if the firm sends a personalized greeting in an email advertisement along with a targeted product recommendation.

To account for the impact of various observable and unobservable consumer specific characteristics, we propose a two stage decision model using a hierarchical Bayesian framework. The key novelty of our model is that it allows us to estimate the parameters at individual level. We identify three segments of consumers
based on their privacy consciousness—privacy conscious, loyal and moderate; the managerial implication here is that different customers prefer different types of personalization and the firm should recognize this while personalizing email advertisements. In short, our analysis shows that personalization is not always a magic bullet which will convert all ‘browsers to buyers’—as the personalization vendors would like us to believe.

A limitation of this study is that we only measure the impact of personalization in the context of email advertisements. As mentioned in the introduction, internet personalization is a broad term and includes other practices such as recommendations, banner advertisements and content personalization. Firms typically use two types of consumer information for personalization—personal information such as name, demographics and location, and product preference information. Personalization can also be classified as intrusive or non-intrusive, depending on whether the customer is made aware that the firm is using her information to offer a personalized experience. A permutation of these options can give rise to many different personalization scenarios each with its own privacy implications. However, our research takes the first step in measuring the business value of personalization and our model can extend to other types of personalization as well.
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APPENDIX A (Essay 1)

Demand in Regions I and III:

**Region I:** For Region I, \( p_1^1 < p_1 < p_1^2 \) and \( p_1^3 < p_1 < p_1^4 \). The demand for firm 1 and firm 2 are given as:

\[
D_1 = x_1 + \frac{1}{x_1} \int (1 - \theta(x)) \, dx, \quad D_2 = \frac{1}{x_1} \int \theta(x) \, dx
\]

In this region, the demand \( D_1 \) is concave in price.

**Region III:** For Region III, \( p_1^3 < p_1 < p_1^4 \) and \( p_1^2 < p_1 < p_1^4 \). The demand for firm 1 and firm 2 are given as:

\[
D_1 = \int (1 - \theta(x)) \, dx, \quad D_2 = x_2 + \frac{1}{x_2} \int \theta(x) \, dx
\]

In this region, the demand \( D_1 \) is convex in price.

Test for Equilibrium in Regions I and III:

In this section, we calculate the equilibrium prices in Regions I and II and verify whether the conditions as outlined above are satisfied. Consider Region I. The demand \( D_1 \) and \( D_2 \) are given as follows:

\[
D_1 = 1 - \frac{(p_1 - p_2 + t)^2}{4(q_1 - q_2)}; \quad D_2 = \frac{(p_1 - p_2 + t)^2}{4(q_1 - q_2)}
\]

Maximizing the profit function by taking first order conditions, the equilibrium prices are given as:

\[
p_1 = \frac{1}{8} (-5t + 3\sqrt{16q_1 - 16q_2 + t}); \quad p_2 = \frac{1}{8} (t + \sqrt{16q_1 - 16q_2 + t})
\]

Verify the conditions for region 1, i.e., \( p_1 \) should be greater than \( p_1^1 \), and less than \( p_1^2 \) and \( p_1^3 \). Taking the values of \( p_1^1, p_1^2 \) and \( p_1^3 \) from equation (3), the following conditions should be satisfied: \( p_1 - p_2 > t \), \( p_1 - p_2 < t \) and \( p_1 - p_2 < q_1 - q_2 - t \).

Substituting the values of \( p_1 \) and \( p_2 \) from above, we note that the first condition is always satisfied, the second condition is satisfied for \( \gamma = \frac{q_1 - q_2}{t} < 1.5 \) and the latter condition is satisfied for \( \gamma > 3 \). Clearly, the second and third conditions are incompatible and hence there exists no equilibrium in region I.

Similarly, we can show that there exists no equilibrium in Region III. We repeat the above analysis with personalization and also under the LI market structure and the results still hold.

**Proof of Proposition 1a:**

Consider the demand in \( R^h_\mu \) as follows: Take any indifference line \( \theta(x) \) in \( R^h_\mu \) intersecting \( \theta(x) = 0 \) and \( \theta(x) = 1 \) at \( x_1 \) and \( x_2 \) respectively. This is as shown in the Figure 1a above. By calculation,

\[
x_1 = \frac{p_2 - p_1 + t}{2 \cdot t}; \quad x_2 = \frac{p_2 - p_1 + t + q_1 - q_2}{2 \cdot t}
\]

The demands \( D_1 \) and \( D_2 \) are:
\[ D_1 = x_1 + \int_{x_i}^{x_2} (1 - \theta) \, dx; \quad D_2 = 1 - x_2 + \int_{x_1}^{x_2} \theta \cdot dx. \] Therefore profits can be expressed as

\[ \pi_1 = D_1 \cdot p_1; \quad \pi_2 = D_2 \cdot p_2. \]

We solve the two stage model using backward induction, i.e., we first solve for prices and then for quality.

**Stage 2:** Taking the first order conditions (FOC) of firm profits w.r.t. \( p_1 \) and \( p_2 \), and solving for prices, we get

\[ p_1 = \frac{6 \cdot t + q_1 - q_2}{6}; \quad p_2 = \frac{6 \cdot t - q_1 + q_2}{6}. \]

Substituting these values of \( p_1 \) and \( p_2 \) in the profit function, we get,

\[ \pi_1 = \frac{(6 \cdot t + q_1 - q_2)^2}{72 \cdot t}; \quad \pi_2 = \frac{(6 \cdot t - q_1 + q_2)^2}{72 \cdot t}. \]

**Stage 1:** Next, we solve for quality. It is easy to verify that \( \frac{\partial \pi_i}{\partial q_i} > 0 \), where \( i = 1,2 \). In other words, the profits of both firms are increasing in their own quality, irrespective of the other firms’ quality level. Thus both firms choose quality as \( q_1 = q_2 = \bar{\theta} \), i.e., both firms choose maximal level of quality. This result is the classical case of \( MaxMin \) differentiation where firms are maximally differentiated on one dimension (horizontal) and minimally differentiated on the other dimension (vertical). Neven et al 1990 predict that it is optimal for firms to adopt a \( MaxMin \) strategy rather than a \( MaxMax \) strategy.

To verify the correctness of the equilibrium for Region \( R^h_{II} \), we need to verify the following conditions: one, the slope of the indifference curve is greater than 1, i.e. \( \frac{2t}{q_1 - q_2} > 1 \), or \( \gamma < 2 \); two, the price offered by firm 1 should satisfy the condition that \( p_1^2 < p_1 < p_1^3 \) as shown in Figure 2a; and three, both \( x_1 \) and \( x_2 \) lie between 0 and 1. Since both firms offer the same quality level, i.e., \( q_1 = q_2 \), there is no vertical differentiation in the market, i.e., \( \gamma = 0 \). Therefore the condition \( \gamma < 2 \) always holds in this case.

**Calculations for Consumer Surplus:**

Consider the LD case. Under, HD none of the firms find it optimal to personalize. Both firm choose the maximum level of quality \( \bar{\theta} \) and price at \( p_1=p_2=t \). Therefore, the CS for customers who buy from firm 1 is given as:

\[ \int_{0}^{1/2} \int_{0}^{1} \left( R + \theta \cdot q_1 - t (1 - x) - p_1 \right) dx \, d\theta. \]

Similarly, we can compute the surplus for consumers who buy from firm 2.
and add these to get the total consumer surplus. The total consumer surplus is \( R + \frac{\theta}{2} - \frac{5t}{4} \). Since, we wish to express the CS in terms of the Q-F Ratio, we can substitute \( \tilde{\theta} = \gamma t + q_2 \). Therefore, the total consumer surplus is:

\[
CS = R + \gamma \cdot t / 2 - 5t / 4
\]

Outline of proof for Proposition 7a

Consider the case of VD and LI when the high quality firm personalizes. The equilibrium profits are given as:

\[
\pi_1^{\text{new}} = \pi_1 - c(q_1); \pi_2^{\text{new}} = \pi_2 - c(q_2)
\]

Substituting from Proposition 5,

\[
\pi_1^{\text{new}} = \frac{(8 \cdot \tilde{\theta} - 8 \cdot \theta + t \cdot \delta)^2}{144 (\theta - \theta)} - c(q_1); \pi_2^{\text{new}} = \frac{(4 \cdot \tilde{\theta} - 4 \cdot \theta - t \cdot \delta)^2}{144 (\theta - \theta)} - c(q_2).
\]

To verify how equilibrium quality level changes with \( \delta \), we derive the expression for \( \frac{\partial \pi}{\partial \delta} \) as follows:

\[
\frac{\partial \pi}{\partial q} = 0 \Rightarrow \left( \frac{\partial^2 \pi}{\partial q^2} \right) \frac{\partial q}{\partial \delta} + \left( \frac{\partial^2 \pi}{\partial q \partial \delta} \right) \frac{\partial \delta}{\partial \delta} = 0 \Rightarrow \frac{\partial q}{\partial \delta} = -\frac{\left( \frac{\partial^2 \pi}{\partial q \partial \delta} \right)}{\left( \frac{\partial^2 \pi}{\partial q^2} \right)}.
\]

Using the profit expression above, we can show that

\[
\frac{\partial q}{\partial \delta} = -\frac{-t \cdot \delta / 72 (q_1 - q_2)^2}{[t \cdot \delta^2 / 72 (q_1 - q_2)^3] - c''(q_1)}.
\]

The numerator is negative. The sign of the denominator depends on the \( \left( \frac{\partial^2 \pi}{\partial q_1^2} \right) - c''(q_1) \) term. Since

\[
\frac{\partial \pi_1}{\partial q_1} - c'(q_1) = 0 \quad \text{at} \quad q_1 = q_1^* \quad \text{(equilibrium quality level)} \quad \text{and also} \quad \left. \frac{\partial \pi_1}{\partial q_1} - c'(q_1) \right|_{q_1 < q_1^*} > 0
\]

and

\[
\left. \frac{\partial \pi_1}{\partial q_1} - c'(q_1) \right|_{q_1 > q_1^*} < 0.
\]

Therefore

\[
\left( \frac{\partial^2 \pi_1}{\partial q_1^2} \right) - c''(q_1) < 0.
\]

Hence the denominator is negative and the overall expression for \( \frac{\partial q}{\partial \delta} \) is negative. Therefore, quality level of firm 1 decreases if it adopts personalization. We use the same line of reasoning to verify other results in Section 6.

Proof of Corollary 4

Proof for corollary 4 is straightforward. Profits for firm 1 under LD and HD are as follows:

\[
\pi_1^{\text{new}} = \frac{(q_1 - q_2 - 2t (3 - \delta))^2}{36 (2 - \delta)} - c(q_1)
\]

where \( q_1 \) and \( q_2 \) are equilibrium quality levels. Taking first order condition
with respect to \( \delta \), we can show that 

\[
\frac{\partial \pi_{1}^{new}}{\partial \delta} = \frac{(q_1 - q_2 + 2t(3-\delta))(q_1 - q_2 - 2t(1-\delta))}{36(2-\delta)^2}.
\]

This is greater than zero only if the term \( q_1 - q_2 > 2t(1-\delta) \). At \( \delta = 0 \), LHS is zero and RHS is +ve. At \( \delta = 1 \), LHS is +ve and RHS is zero. Since both LHS and RHS are monotonic in \( \delta \), there exists one value of \( 0 < \delta < 1 \) where \( \frac{\partial \pi_{1}^{new}}{\partial \delta} > 0 \).
APPENDIX (Essay 2)

Proof of Proposition 1
Suppose firm 1 personalizes for customers in the PS segment. $p_1$ and $p_2$ are the prices charged by firms 1 and 2 respectively. We proceed by finding the indifference point in the PS and the PC segments. In the PS segment, customers receive a personalized product from firm 1 (utility is given as $U = r - p_1$) and a standard product from firm 2 (utility is given as $U' = r - p_2 - (1+x)$). The indifference points for the PS and PC segments of consumers are $x$ and $y$ respectively where $x$ and $y$ are obtained by solving $r - p_1 = r - p_2 - (1-x)$ and $r - p_1 - y = r - p_2 - (1-y)$ respectively. Therefore, the indifference point $x$ is given as $x = p_2 - p_1 + 1$ and $y$ is given as $y = (p_2 - p_1 + 1)/2$.

Profits of firm 1 and firm 2 are given as $\pi_1 = p_1 ((1 - \beta) \cdot x + \beta \cdot y)$; $\pi_2 = p_2 ((1 - \beta) \cdot (1-x) + \beta \cdot (1-y))$. Taking first order conditions and solving for prices, we obtain the equilibrium prices when one firm in the market is capable of offering a personalized product.

$p_1 = \frac{4 - \beta}{3(2 - \beta)}; p_2 = \frac{2 + \beta}{3(2 - \beta)}$. Firm profits at the equilibrium prices are $\pi_1^{PS} = \frac{(4 - \beta)^2}{18(2 - \beta)}; \pi_2^{PS} = \frac{(2 + \beta)^2}{18(2 - \beta)}$.

where $\pi_1^{PS}, \pi_2^{PS}$ are profits of firm 1 and firm 2 when firm 1 offers a personalized product to all customers in the PS segment.

If firm 1 decides not to offer a personalized product to the PS segment, the indifference points are given as $x = y = (p_2 - p_1 + 1)/2$ Maximizing the above profit function with respect to firm prices, we obtain the equilibrium price when none of the firms personalizes. $p_1 = p_2 = 1$. The profits are $\pi_1^{SS} = \pi_2^{SS} = \frac{1}{2}$, where $\pi_1^{SS}, \pi_2^{SS}$ are profits of firm 1 and firm 2 when both firms offer a standard product.

Comparing profits in the two cases above, we find that both firms earn higher profits when firm 1 does not offer a personalized product to customers in the PS segment. Therefore, the overall equilibrium is that both firms choose to offer a standard product.

Proof of lemma 1
Stage II profits are given as $\pi_1 = p_1 ((1 - \beta) \cdot z + \beta \cdot x)$; $\pi_2 = p_2 ((1 - \beta) \cdot (1-z) + \beta \cdot x)$ where $x$ is the indifference point for the $\beta$ consumers and is obtained by solving $r - p_1 - x = r - p_2 - (1-x)$

Maximizing the above profit expressions with respect to firm prices, we get

$p_1^* = \frac{2(1+z) - \beta(2-z-1)}{3\beta}; p_2^* = \frac{2(2-z) + \beta(2z-1)}{3\beta}$. Substituting $p_1$ and $p_2$ in the profit expressions above, we get

$\pi_1 = \frac{(2(1+z) - \beta(2-z-1))^2}{18\beta}; \pi_2 = \frac{(2(2-z) + \beta(2z-1))^2}{18\beta}$

We can show that $\frac{\partial \pi_i}{\partial \beta} < 0$ where $i = 1,2$. Also $\frac{\partial \pi_i}{\partial z} > 0; \frac{\partial \pi_i}{\partial z} < 0$

Proof of lemma 2
From stage 2, firm prices are given as $p_1^* = \frac{2(1+z) - \beta(2z-1)}{3\beta}$; $p_2^* = \frac{2(2-z) + \beta(2z-1)}{3\beta}$. Under these set of prices, firm 1 captures $z$ customers in the PS segment and firm 2 captures $1-z$ customers in the PS segment. If $z$ is large (i.e. $1-z$ is small), firm 2 may find it optimal to deviate from this equilibrium by charging a lower price $p_2^d$ and capturing additional PS customers to the left of $z$. In this case, the indifference points in the PS and PC segments are $x$ and $y$ respectively, where $x = p_2^d - p_1 + 1$; $y = \frac{p_2^d - p_1 + 1}{2}$. The expression of firm 2’s profit when it deviates from the tacit collusion equilibrium is $\pi_2^d = (1-\beta) \cdot p_2^d \cdot (1-x) + \beta \cdot p_2^d \cdot (1-y)$. Substituting the value of $p_1$ as above and solving the first order condition with respect to $p_2^d$, the profit for firm 2 if it deviates is $\pi_2^d = \frac{2 + (2-\beta)(1-\beta) + \beta^2}{18(2-\beta)\beta^2}$. 

Firm 2 will not find it optimal to deviate if this profit is less than the profit that it makes in the ‘tacit collusion’ equilibrium given in proposition 2, i.e. if $\pi_2^d \leq \pi_2$. Solving for $z$, we obtain the following:

$z \leq z^* \left( = \frac{4 + \beta(14 - \beta)(10 - \beta)) - 3(4 - \beta)(2-\beta)\sqrt{\beta(2-\beta)}}{(2-\beta)(1-\beta)(5\beta - 2) \right)$

**Proof of lemma 3**

We now show that if $z^*$ is low enough, firm 1 can find it optimal to deviate from the tacit collusion equilibrium and capture additional customers to the right of $z^*$. Mathematically, this can be shown as follows:

Let $p_1$ and $p_2$ be the prices under the tacit collusion equilibrium as given in lemma 2. Firm 1 offers a personalized product to customers to the left of $z$ in the PS segment and both firms offer a standard product to customers to the right of $z$ in the PS segment and to customers in the PC segment. The incentive compatibility condition for firm 1 is as follows:

Let firm 1 charge a price $p_1^{dev} < p_1$ such that it captures customers to the right of $z$. The indifference point in the PS segment is now given as $x = \frac{p_2 - p_1^{dev} + 1}{2}$ (which is the same as the indifference point in the PC segment). Firm 1’s profits by deviating are given as: $\pi_1^{dev} = (1-\beta) \cdot p_1^{dev} \cdot x + \beta \cdot p_1^{dev} \cdot x = p_1^{dev} \cdot x$. Substituting $p_2^* = \frac{2(2-z) + \beta(2z-1)}{3\beta}$ which is the price charged by firm 2 under the tacit collusion equilibrium, and solving the first order condition w.r.t. $p_1$, we obtain $p_1^{dev} = \frac{2 - z(1-\beta) + \beta}{3\beta}$ and $\pi_1^{dev} = \frac{(2 - (1-\beta)x + \beta)^2}{18\beta^2}$. Comparing this profit with the profit under tacit collusion, we find that firm 1 always finds it profitable to deviate if $z^* < z^{**}$ where $z^{**}$ is given as $z^{**} = \frac{2 + \beta}{1 + 2\beta + 3\sqrt{\beta}}$.
Deviation from Tacit Collusion Equilibrium (TCE):

Here we show that it is indeed optimal for both firms not to deviate from the tacit collusion equilibrium, TCE. Let $p^*_1$ and $p^*_2$ be the price charged by firms 1 and 2 respectively under the TCE. From Lemma 1, 

$$
p^*_1 = \frac{2(1+z) - \beta(2z - 1)}{3\beta}; \quad p^*_2 = \frac{2(2-z) + \beta(2z - 1)}{3\beta},
$$

where $z$ is the scope of personalization chosen by firm 1 (From lemma 2, we know that $z^* = \frac{4 + \beta(14 - \beta(10-\beta)) - 3(4-\beta(2-\beta))\sqrt{\beta(2-\beta)}}{(2-\beta)(1-\beta)(5\beta - 2)}$).

In this proof, we show that given $z$ and $p^*_1$ chosen by firm 1, firm 2 earns the maximum profit by pricing at $p^*_2$ and capturing $1-z$ fraction of the market.

Suppose firm 2 captures a fraction $1-v$ of the market where $1-v > 1-z$ (i.e. $v$ lies to the left of $z$). In other words, firms 2 prices such that some customers to the left of $z$ who receive a personalized product from firm 1 buy from firm 2. In the proof of Lemma 2, we showed that such deviation by firm 2 is not profitable because firm 2 gets at least as much profits after deviation as under TCE. Therefore firm 2 does not find it more profitable to deviate by pricing lower and capturing customers to the left of $z$.

Next we consider the case where firm 2 can price higher than $p^*_2$ and gain a market share equal to or lower than $1-z$. For a customer located at $w (\geq z)$, firm 2 can charge a higher price $p^*_2 = p^*_1 + w$ such that it capture all $1-w$ customers located to the right of $w$. In this revised scenario, profits of firm 2 are given as 

$$
\pi^{\text{dev}}_2 = (p^*_1 + w)[(1-\beta)(1-w) + \beta\cdot\left(1 - \frac{p^*_2 - p^*_1 + 1}{2}\right)].
$$

Taking first order conditions w.r.t $w$, we can show that 

$$
\frac{\partial \pi^{\text{dev}}_2}{\partial w} < 0
$$

for all values of $p^*_1$ and $\beta$. In other words, firm 2 captures a fraction of market $1-w$ (i.e. $1-z$).

Therefore, we consider the case that firm 2 prices at $p^*_1 + z$ and captures all customers to the right of $z$. Firm 2 profits are given as 

$$
\pi^{\text{dev}}_2 = (p^*_1 + z)[(1-\beta)(1-z) + \beta\cdot\left(1 - \frac{p^*_2 - p^*_1 + 1}{2}\right)] .
$$

Substituting $p^*_2 = p^*_1 + w$, 

$$
p^*_1 = \frac{2(1+z) - \beta(2z - 1)}{3\beta},
$$

we find that 

$$
\pi^{\text{dev}}_2 = \frac{(2-\beta)(1-z)(2+\beta-z(2-\beta))}{6\cdot\beta},
$$

where 

$$
z^* = \frac{4 + \beta(14 - \beta(10-\beta)) - 3(4-\beta(2-\beta))\sqrt{\beta(2-\beta)}}{(2-\beta)(1-\beta)(5\beta - 2)}.\!
$$

We show that $\pi^{\text{dev}}_2 \leq \pi^\text{TCE}_2$.

Thus we show that the TCE is a Nash equilibrium and any deviation from the same is not profitable. Similarly, we can show that any deviation by firm 1 is not profitable.

Proof of lemma 4

The proof proceeds similar to lemma 2. The intuition is that firm 1 chooses to transfer information about a faction of customers to firm 2 such that both firms offer a personalized product to their respective fraction and a standard product to the rest of the market. Under such a scenario, if $1-x_0$ is the amount of information transferred to firm 2 and Sunil Wattal,
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under equilibrium firm 1 captures customers to the left of $x_0$ and firm 2 captures customers to the right of $x_0$, then the profits are given as $\pi_1 = p_1((1 - \beta) \cdot x_0 + \beta \cdot x)$; $\pi_2 = p_2((1 - \beta) \cdot (1 - x_0) + \beta \cdot (1 - x))$ where $x$ is the indifference point for the $1 - \alpha$ consumers and is obtained by solving $r - p_1 - x = r - p_2 - (1 - x)$

**Proof of Proposition 4**

The consumer surplus is calculated as follows: Under information sharing, in the PS segment, a fraction $x_0$ of consumers receives a personalized product from firm 1 and the rest $1 - x_0$ consumers receive a personalized product from firm 2. The consumer surplus of the PS consumers who buy from firm 1 (firm 2) is given as

$$\int_{0}^{x_0} (r - p_1)dx$$

$$\left(\int_{x_0}^{1} (r - p_2)dx\right)$$

where $p_1$, $p_2$ and $x_0^*$ have the same values as given in propositions 2 and 3.

Similarly, the consumer surplus for consumers in the PC segment who buy from firm 1 (firm 2) is given as

$$\int_{0}^{x_0} (r - p_1 - x)dx$$

$$\left(\int_{x_0}^{1} (r - p_2 - 1 + x)dx\right)$$

where $p_1$, $p_2$ and $x$ have the same value as in proposition 1.

Total consumer surplus under information sharing is

$$CS = (1 - \beta)\int_{0}^{x_0} (r - p_1)dx + (1 - \beta)\int_{x_0}^{1} (r - p_2)dx + \beta\int_{x_0}^{1} (r - p_1 - x)dx + \beta\int_{x_0}^{1} (r - p_2 - 1 + x)dx$$
TECHNICAL APPENDIX A1 (Essay 3)

I. Priors and Posteriors in Stage 1

Priors

We specify conjugate priors on $\psi$ and $V_\theta$ as follows:

\[
\text{vec}(\psi) \sim N(\text{vec}(\psi), V_\theta \otimes A^{-1})
\]

\[
V_\theta \sim IW(\nu, V)
\]

We need to specify priors over the hyper-parameters $\nu, V, \psi$ and $A^{-1}$. $\psi$ represents the effect of observable consumer specific variables on model coefficients, $\theta_n$. We do not have any information on the magnitude or sign of the $\psi$ coefficients. Therefore, a priori we specify $\psi = 0$. Further, we specify a diffuse prior on $\psi$ by specifying a small value for the precision parameter $A$. Moreover, we choose diffuse priors on $V_\theta$ by choosing an Inverted Wishart distribution with small degrees of freedom, following recommendations from Rossi et al, 1996:

- $\nu = \text{number of } \Delta \text{coefficients (nvar)} + 3$
- $V = \nu \cdot \text{diag(nvar)}$, where diag(nvar) is a diagonal matrix of dimension nvar.
- $\psi = 0$
- $A^{-1} = 100 I$

Conditional Posteriors

We use a hybrid ‘Metropolis within Gibbs’ MCMC method for constructing the Markov chain.

Step I: Draw $\theta_n | y, X, V_\theta, \psi, Z$

\[
\pi(\theta_n | y, X, V_\theta, \psi, Z) \propto l(y | X, \theta_n) \cdot \pi(\theta_n | V_\theta, \psi, Z)
\]

This equation simply states that the density of $\theta_n$ given $y$ can be expressed as the probability of $y$ conditional on $\theta_n$ (which is also the likelihood of the ordered probit model) times the probability of $\theta_n$. 

\[
l(y | X, \theta_n) = \prod_{n=1}^{N} \prod_{j=1}^{J_n} \left( \Phi(\theta_n \cdot X_{jn}) \right)^{y_{jn}}
\]  

Since the distribution of $\theta_n$ is $\theta_n \sim N(\psi \cdot Z_n, V_\theta)$, we can write

\[
\pi(\theta_n | V_\theta, \psi, Z) \propto |V_\theta|^{1/2} \exp\left\{ -\frac{1}{2} (\theta_n - \psi \cdot Z)^\top V_\theta (\theta_n - \psi \cdot Z) \right\}
\]

Since (6) is not a standard normalized joint density, we use the Metropolis-Hasting algorithm (Tierney 1994; Chib and Greenburg, 1995) for sampling from non-standard full conditionals. Also, since we specify conjugate prior distributions on $\Delta$ and $V_\theta$, we draw these using Gibbs sampling as follows:

Step II: Draw $V_\theta | \theta_n, \psi$
\[ V_{\theta|\theta_n, \psi} \sim IW(v + N, V + S) \] where \( N \) is the number of rows in \((\theta_n)\), which is also equal to the number of users. Also, \( S = (\theta_n - \psi \cdot Z)'(\theta_n - \psi \cdot Z) \)

**Step III:** Draw \( \psi|V_{\theta}, \theta_n \)

\[ \psi|V_{\theta}, \theta_n \sim N(\bar{\psi}, V_{\theta} \otimes (Z'Z + A)^{-1}) \] where \( \bar{\psi} = (Z'Z + A)^{-1}(Z'Z\psi + A\overline{\psi}) \) and \( \bar{\psi} = (Z'Z)^{-1}Z'\theta_n \)

### II. Priors and Posteriors in Stage 2

**Priors**

In Stage 2, we specify the priors following a logic similar to that in Stage 1. E.g. we specify conjugate priors on \( \Delta \) and \( V_\delta \) as follows: \( \text{vec}(\Delta) \sim N(\text{vec}(\overline{\Delta}), V_\delta \otimes A^{-1}) \) and \( V_\delta \sim IW(v, V) \)

The priors on the hyper-parameters \( v, V, \overline{\Delta} \) and \( A^{-1} \) are specified as:

- \( v = \) number of \( \Delta \)-coefficients (\( nvar \)) + 3
- \( V = v^*\text{diag}(nvar) \), where \( \text{diag}(nvar) \) is a diagonal matrix of dimension \( nvar \).
- \( \overline{\Delta} = 0 \)
- \( A^{-1} = 100 I \)

**Conditional Posteriors**

We use a hybrid ‘Metropolis within Gibbs’ MCMC method for constructing the Markov chain. Prior research has shown that using a pure Gibbs chain can be slow to converge (Cowles 1996). Liu et al (1994) proposed a ‘collapsed’ Gibbs sampler method in which \( \beta_n \) and \( \alpha_n \) are generated together from their joint posterior distributions as follows.

**Step I:** Draw \( \delta_m|y, W, V_\delta, \Delta, Z \)

\[ \pi(\delta_m|y, W, V_\delta, \Delta, Z) \propto l(y|W, \delta_m) \cdot \pi(\delta_m|V_\delta, \Delta, Z) \]

This equation simply states that the density of \( \delta_m \) given \( y \) can be expressed as the probability of \( y \) conditional on \( \delta_m \) (which is also the likelihood of the ordered probit model) times the probability of \( \delta_m \).

\[
l(y|W, \delta_m) = \prod_{m=1}^{M} \prod_{k=1}^{K_m} \prod_{h=1}^{4} \left[ \Phi(\alpha_{mh} - \delta_m \cdot W_{km}) - \Phi(\alpha_{mh-1} - \delta_m \cdot W_{km}) \right]^{R_{kh}}
\]

where \( R_{kh} = 1 \) if \( V_k \) falls in \( h^{th} \) category

\[ = 0 \text{ otherwise} \]

Since the distribution of \( \delta_m \) is \( \delta_m \sim N(\Delta \cdot Z, V_\delta) \), we can write

\[ \pi(\delta_m|V_\delta, \Delta, Z) \propto |V_\delta|^{1/2} \exp\left\{ -\frac{1}{2} (\delta_m - \Delta Z)'V_\delta (\delta_m - \Delta Z) \right\} \]
Since (7) is not a standard normalized joint density, we use the Metropolis-Hasting algorithm (Tierney 1994; Chib and Greenburg, 1995) for sampling from non-standard full conditionals. The posterior distributions on $\Delta$ and $V_\alpha$ are drawn using the Gibbs sampler similar to Steps II and II in Stage 1 above.

**Appendix 1 (Essay 3)**
The Figure below shows a sample email. On the top is firm A’s corporate logo. Some emails have a personalized greeting, which is the customer’s name. This email features an offer for long distance phone plans. Therefore, this email also has product personalization for customers in the ‘long distance’ pool.

---

**Firm A's Logo**

Dear <GREETING>,

Tired of hearing about yet about your Long Distance carrier's continuous string of problems and wondering when their problems will affect you? You could switch, but how do you know your new carrier won't have the same problems?

ZoneLD, 's premier Long Distance partner, utilizes multiple underlying carriers to carry your long distance call. Therefore, you can rest easy knowing your provider has alternatives. All this, with savings of 40% or more on your long distance (as compared with the most popular residential plans).

Don't wait to switch!

---

**brings you a long distance service that offers:**
- Cost per minute - as low as 4 cents per minute
- Monthly charge - None
- Billing increments - 6 second increments
- Minimum call length - 6 seconds
- Multiple carrier network - YES

**PLUS**
- Bonus - 300 FREE minutes in your third month of service
- Online account management

To learn more about this long distance offer [CLICK HERE](#)