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The Effect of Economic and Relational Direct Marketing Communication on Buying Behavior in B2B Markets

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The Effect of Economic and Relational Direct Marketing Communication

on Buying Behavior in B2B Markets

BY

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ACCEPTANCE

This dissertation was prepared under the direction of *Kihyun Hannah Kim's* Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

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Committee Chair: *Dr. V. Kumar*

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Business to Business (B2B) firms spend significant resources managing close relationships with their customers, yet there is limited understanding of how the customers perceive the relationship based on the customer management efforts initiated by the firm. Specifically, studies on how firms communicate different values to B2B customers and how they perceive the values the firm offers by consistently evaluating the direct marketing communication which ultimately affect their buying behaviors have been largely overlooked. Typically, the direct marketing communication efforts are geared towards explicitly featuring *economic values* or *relational values*. To implement an effective communication strategy catering to customers' preferences, firms should understand how these organizational marketing communications dynamically influence the perceived importance of different values offered by the firm. Therefore, using data from a Fortune 500 B2B service firm and employing a content analysis and a robust econometric model, we find that (i) the effect of economic and relational marketing communication on customer purchase behavior vary by customers and change overtime (ii) the latent stock variable of direct marketing communication affect the customer purchase behaviors and (iii) the evolution of customers' perceived importance can be recovered using the transaction data. Overall, we provide a marketing resource reallocation strategy that enables marketers to customize marketing communication and improve a firm's financial performance.

Keywords: B2B, Marketing Strategy, Direct Marketing Communication, State Space Model, Customer Relationship Management

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INTRODUCTION

The importance of acquiring and cultivating profitable relationships is paramount especially in Business-to-Business (B2B) environments for several reasons. First, B2B markets are characterized by fewer clients[1] and purchases, but larger transaction quantities compared to B2C markets (Järvinen et al. 2012). Thus, B2B sellers tend to allocate greater resources (e.g., time, effort and dollars) toward gathering and processing information on B2B customers (i.e., buyers) to understand their needs and successfully sell the company's products or services. Second, the interactions between the clients and the firms are more frequent in B2B markets than B2C market and that B2B customers constantly evaluate the B2B firms based on their experience with the firms (Bolton, Lemon, and Bramlett 2006). Finally, to build and maintain long-term relationships with B2B customers, B2B firms contact their clients one by one and provide customized and personalized marketing. Hence, B2B markets have been known a fruitful context of applying the principles of customer relationship management (CRM) by offering tailored services at different time points to relatively smaller set of customers. This leads B2B customers to process information delivered from the firm and adjust their perceptions and behavior accordingly.

Interestingly, based on managerial interviews and a review of literature, we find that B2B customers perceive the values the firm offers by consistently evaluating the organizational marketing communication (Dwyer, Schurr, and Oh 1987). To minimize customer churn and increase the profits, B2B firms use direct marketing efforts (i.e., email, phone, and in-person etc.) to interact with clients. Typically, the direct marketing communication is geared towards explicitly featuring *economic values* or *relational values* (Bolton, Smith, and Wagner 2003;

[1] The terms "clients" and "customers" are used interchangeably.

Dwyer, Schurr, and Oh 1987; Gassenheimer, Houston, and Davis 1998). Economic values include the monetary aspects of the direct marketing communication messages (e.g., promotion) which are evaluated by the rational judgement of the customers. Relational (social) values are the non-monetary aspect of the direct marketing communication messages (e.g., support service) which evokes emotional responses (Liu 2006; Ulaga and Chacour 2001). Accordingly, we conceptualize two dimensions of organizational direct marketing communication: *economic* and *relational* marketing communications.

Based on customers' prior experience and intrinsic preferences, these customers formulate the perceived importance of the economic and relational values offered, which in turn influence their purchase behaviors (Bolton, Lemon, and Verhoef 2008). However, prior studies investigating the dynamic effects of marketing communication evaluate only one specific type of marketing activities such as price negotiations (Zhang, Netzer, and Ansari 2014) and social marketing contacts (Luo and Kumar 2013) in B2B markets. Yet, analyzing how the clients are reached by looking at the overall content of the direct marketing communication has been largely overlooked in the prior literature. Therefore, to customize marketing messaging based on each customer's preferences, it is important to understand what has been explicitly featured in each marketing communication and find the differential effects of marketing communication efforts by the values emphasized and provided. All customers do not require the same level or the same kind of marketing communication due to their past experiences and underlying customers' perceptions. Thus, to build strong and profitable B2B relationships, firms also need to consistently engage in direct marketing communication that fit customers' preferences, help foster positive perceptions, influence purchase behavior, and, eventually, improve financial performance (Narayandas and Rangan 2004).

To implement an effective communication strategy catering to customers' preferences, firms should understand how organizational marketing communications influence consumers' perceived importance of different values offered by the firm. While there have been several studies investigating the role of perceptions in the B2B setting, the studies heavily relied on cross-sectional surveys (Mende, Bolton, and Bitner 2013; Palmatier 2008). Survey-based measures of perceptions, though informative, are costly to collect and may be biased (Park and Srinivasan 1994). Additionally, past research focusing on perceptions has largely overlooked the evolving nature of customer perceptions (Hennig-Thurau and Klee 1997). It is, nevertheless, important for firms to develop a holistic view of B2B relationship development as well as the dynamic nature of customers' perceptions. Specifically, to our knowledge, the creation and evolution of perceived importance of different values offered by marketing communications have not been studied empirically in the marketing literature.

Therefore, we seek to address the following research questions:

(1) Are there *differential* effects of economic and relational marketing communications on customer purchase behavior?
    a. Are these effects different across *customers*?
    b. Do these effects change over *time*?
    c. Is there a synergy between economic and relational marketing communication?
(2) Can we assess the *long-term* effects of economic and relational marketing communication?
(3) Can we uncover the evolving nature of the customers' perceived importance using the transaction data and not relying on surveys?
(4) If uncovered, how does the perceived importance moderate the effects of economic and relational direct marketing communication on customers' purchase behavior?
(5) How can marketers *leverage* the findings from the aforementioned research questions to manage marketing resources and improve a firm's financial performance?

There are three unique contributions to the literature. First, we empirically identify the economic and relational direct marketing communication by employing a content analysis. We analyze the qualitative comments in the direct marketing communication efforts and categorize the content of the messaging based on the definition provided in the prior literature. Second, we study the dynamic and heterogeneous effects of two different marketing communication efforts in a single modeling framework which has not been used so far. In doing so, we also account for the marketing endogeneity issue and estimate the dynamic parameters using a Bayesian approach. Third, we empirically uncover the latent stock of firm's direct marketing efforts on purchase behavior and how customers evaluate the importance of the value provided by the firm using the state space modeling approach. We further conduct an internal validation for the uncovered perceived importance measures.

We address the research questions by empirically analyzing a unique customer level dataset of a Fortune 500 B2B service firm. The dataset contains rich information consisting of customer-level transactions, direct marketing communication interventions, and customer characteristics over an observation period of 4 years. We find that not all clients respond favorably to economic marketing communications or relational marketing communications. Each client respond very differently to direct marketing communication based on its experience to the firm's past marketing efforts. We also find the importance of accounting for the dynamic effects of direct marketing communication. Therefore, we offer guidelines for managers in terms of how much, when, and to whom the two types of marketing communication should be deployed.

The rest of the paper is organized as follows. First, we review the prior research related to the current study and discuss the gaps in the academic literature. Then, we develop the conceptual framework and state the propositions that form the basis of our study. Next, we describe the data and the key measures employed in this research and show our modeling approach. We then present the estimation results and discuss managerial implications of the research. We conclude with the limitations and future directions of this research.

RELATED LITERATURE

Economic vs. Relational Marketing Communication

Given the large amount of dollars spent toward building customer relationships, it becomes critical that managers have a clear understanding of how the customers are reached by the firm and keep track of the direct marketing communication efforts. There have been a number of studies that examine the influence of firm initiated marketing efforts on customers' purchase behavior in a B2B setting. For example, Venkatesan, Kumar, and Bohling (2007) study the effects of marketing programs on purchase timing and quantity decisions by categorizing the firm initiated contacts as rich modes and standard modes, depending on whether the contacts were made through salespeople, telephone and/or direct mails. Kumar et al. (2011) investigate the relationship between marketing investments and total amount purchased. Much of the past work in the B2B area has studied marketing communication as *aggregate* marketing without differentiating the core values offered (Kumar et al. 2011) or focused on specific contact modes such as direct mail or email (Venkatesan, Kumar, and Bohling 2007). However, there is relatively little literature studying the core value communicated through each of the direct marketing contacts.

Marketing communication in B2B settings can be broadly classified based on the types of customer benefits offered (Bolton, Smith, and Wagner 2003; Gwinner, Gremler, and Bitner 1998) and the types of customer bonds being formed (Berry 1995). Gwinner, Gremler, and Bitner (1998) suggest that from the customer's perspective, relational benefits (e.g., social, psychological, and customized benefits) and economic benefits motivate customers to maintain a relationship with a firm. Bolton, Smith, and Wagner (2003) propose that firms categorize the resources exchanged with the customers as either economic or social and investigate the effects through experimentally generated scenarios on how these economic and social categories of service resources influence the customers' evaluations of business relationships. Additionally, Berry (1995) introduces three aspects of relationship marketing: financial, social, and structural relationship marketing programs. Adopting Berry (1995)'s definition, Palmatier, Gopalakrishna, and Houston (2006) empirically test the direct impact of these different relationship marketing activities on customer specific returns. In a B2C context, Rust and Verhoef (2005) study the heterogeneity of responses across two types of marketing interventions, action-oriented and relationship-oriented interventions. They consider the direct mailing as the action-oriented intervention given that it provides short-term economic rewards and the relationship magazine as the relationship-oriented intervention given that it focuses on providing social benefits. To account for the wide range of marketing communications that firms engage in, academics have acknowledged that it is important to conceptualize organizational efforts along a fixed number of dimensions. Hence, following the definition established by many marketing scholars (Bolton, Smith, and Wagner 2003; Dwyer, Schurr, and Oh 1987; Gassenheimer, Houston, and Davis 1998), we propose to study two types of direct marketing communication: *economic* and *relational* marketing communication that encompasses various direct marketing communication efforts initiated by a firm.

Economic marketing communication is the firm's outbound marketing communication that are aimed toward making the relationship more financially attractive by delivering messages that are focused on economic (i.e., monetary) incentives such as price discounts, offering better products, or providing cost reduction opportunities. On the other hand, *relational* marketing communication is the firm's outbound marketing communication aimed toward building more personal relationships with clients. Regular check-ups, seeking personal feedbacks, advising on special features and customizing benefits to expand personalized relationships and increasing noneconomic satisfaction can be considered as relational (social) marketing communication.

In Table 1, we provide a summary of related prior work focused on empirically studying the effects of marketing efforts focusing on either economic or relational value, or both in the B2B settings. To the best of our knowledge, no studies have empirically analyzed the content of the direct marketing communications to identify the different values offered by firm employees in B2B markets. We believe that this dearth is mainly due to the complexity of B2B transactions/ decision making and unavailability of longitudinal data on the firm's marketing communications that have different values offered. B2B firms are known to provide the messages on economic incentives to build the interactions and activate disengaged clients. The social and relational benefits are emphasized to sustain the close interactions with clients in a competitive market. Thus, economic and relational marketing communication efforts cannot survive without each other. Yet, given clients' interests and orientations, the relative importance of these direct marketing communications can vary for each client. Therefore, to provide more relevant messages to each client, we believe it is important to distinguish the relative effects of direct marketing communication efforts on customer purchase behavior.

[Insert Table 1 about here]

Temporal Effects of Direct Marketing Communication

B2B firms foster frequent and direct communications with their customers (Crosby, Evans, and Cowles 1990). However, there have been few studies focusing on the effect of temporal differences in direct marketing communication efforts on customer purchase behavior in the B2B context. Palmatier, Gopalakrishna, and Houston (2006) focus solely on the fixed effects of the firm-initiated actions on customer purchase behaviors without accounting for the customer-level differences and changes in responses to marketing communication. Further, prior literature that study the dynamic effects of marketing has often restricted itself to studying only specific types of marketing activities such as price negotiations (Zhang, Netzer, and Ansari 2014) or frequency of social marketing contacts (Luo and Kumar 2013). As shown in Table 1, there are limited studies addressing how the responses to different types of direct marketing efforts change overtime.

Responses to firm's direct marketing efforts can change over time due to various reasons. Given the large amount of dollars spent toward building customer relationships, it becomes critical that managers have a clear understanding of how customers *perceive* the value communicated through the different direct marketing efforts. Palmatier, Gopalakrishna, and Houston (2006) discuss that marketing activities offering different values can lead to different forms of customer bonds (e.g., financial or social). Bolton, Lemon, and Verhoef (2008) denote the importance of understanding the changes in customers' perceptions as the customers' prior opinions influence responsiveness to new information. That is, depending on how a customer perceives the value provided by the firm, the reaction to new marketing actions can change. Since firms continuously contact customers delivering different values to strengthen customer-firm relationships, it is important to understand the level and the trend of the time-varying effects of economic and relational marketing communication on customer purchase behavior due to the changes in customer perceptions. Even if the firms invest heavily to communicate with clients, clients will not be affected by certain messages (e.g., delivering economic benefits) when their perceived importance of the specific value (e.g., economic value) - which is how they interpret the weight of the value offered by the firm - is low.

Research in psychology and consumer behavior suggests that customers constantly make adjustments to their perceptions based on their prior experience (Folkes 1988). Puccinelli et al. (2009) also find that customers continuously make adjustments to their perceptions based on their experience and use the perceptions to make more effective purchase decisions. Customers formulate perceptions which are the subjective measures for the degree of fit between the offering and their expectations (Steenkamp 1990). Therefore, when customers perceive the message delivered by the firm as valuable and recognize the gratification to their needs, they are more likely to have strong reactions towards the specific marketing communication (Katz, Haas, and Gurevitch 1973). Numerous studies in a B2C context have shown the importance of accounting for the time-varying nature of marketing effectiveness and the changes in customer perceptions when modeling customer behavior. While much of the past research on dynamic models have been implemented in a B2C context (Narayanan, Manchanda, and Chintagunta 2005; Osinga, Leeflang, and Wieringa 2010), the role of dynamics and preference evolution is also important to consider in the B2B space as well.

However, despite its relevance, there are a limited number of empirical studies about the perceptions affected by the direct marketing communication. Prior marketing research has focused on customers' perception of product quality (Mitra and Golder 2006) and service quality (Bolton, Lemon, and Verhoef 2008). Prior empirical work in the B2B space has stressed the importance of understanding the 'dynamics' of marketing (Zhang, Netzer, and Ansari 2014). However, much of prior literature has *discretized* the customer relationships into 'states', while ignoring the *continuous* nature of the dynamics. Luo and Kumar (2013) study the customer's overall assessment of the B2B relationship state formed by past transactions and social marketing contacts which governs customer's purchase decisions. Zhang, Netzer, and Ansari (2014) study the dynamic impact of pricing decisions on customer's purchase decisions which is influenced by the single B2B relationship state. Both studies attempt to address the dynamic problem by assuming 'discrete' customer states that govern the buyer-seller relationships. However, as mentioned in Zhang, Netzer, and Ansari (2014), the relationship dynamics induced by price are different from relationship dynamics triggered by other marketing communication. Thus, the high level of overall perceptions neglects the perceived importance of the different values offered by the firm. If economic and relational values perceived from the marketing communication are blended into one outcome, it is hard to distinguish each customer's preferences towards different values. Hence, treating perceptions to be unidimensional makes it difficult to assess the differential effects of each marketing communication value and adjust the resource allocation strategy.

Furthermore, the firm's direct marketing efforts can have a long-term effect on customers' purchase behavior. Similar to how advertising has a long-term effect on brand preferences (Sriram, Chintagunta, and Neelamegham 2006), marketing investments have been shown to have a carry-over effect on building the brand equity (Leeflang et al. 2009). The volume of online communication has been shown to have long-term effect on sales by creating the demand-generating stock of information (Sonnier, McAlister, and Rutz 2011). Likewise, customers can accumulate the direct marketing communication initiated by the firm which in turn will affect their behavior. Thus, studying how marketing communication efforts cumulatively influence the subsequent purchase of each customer is an important component to understand to quantify the overall effect of direct marketing efforts on each customer.

Therefore, in this study, we underscore the importance of examining the two dimensions of perceived importance, which evolve based on the organizational marketing communications and customer experience, the perceived importance of economic value and relational value. In addition, we also study the long-term effects of direct marketing communication on customer purchase behavior by capturing the latent information stock of direct marketing communication. To the best of our knowledge, there is no study that empirically estimates the dynamics in the customers' latent information stock as well as the perceived importance across the economic and relational dimensions. Therefore, the long-term direct effect of marketing communication efforts on purchase behavior and the moderating effect of perceived importance on the relationship between specific marketing communications and purchase behavior can be explored in the current study. In the following section, we describe the conceptual framework and subsequently develop the dynamic model used in this study.

CONCEPTUAL FRAMEWORK

Our review of the research on direct marketing activities in the B2B market converges into the development of the conceptual model framework as shown in Figure 1. There are three features that are particularly noteworthy about the conceptual model.

[Insert Figure 1 about here]

Heterogeneous Direct Effects of Marketing Communications

First, we study the direct effects of two types of firm initiated marketing communications: economic and relational marketing communication on customer purchase behavior. While it is known that firms indulge in building close relationships with the customer (Luo and Kumar 2013), it is important to recognize *which type of marketing communication influence the relationship in what manner*. As stated earlier, we conceptualize the firm's direct marketing communication along two dimensions to account for the wide range of marketing communication that firms engage in. Given that some customers are motivated to engage in interactions with firms to save money (Gwinner, Gremler, and Bitner 1998), we expect the economic marketing communication in period *t* will have a positive effect on customers purchase revenue in period *t*. Further, as some customers feel positive emotions through the personal and social engagement with the firm's employee (Gwinner, Gremler, and Bitner 1998), the relational marketing communication in period *t* will also have a positive effect on customers purchase revenue in period *t*. However, the relative effectiveness of the two types of direct marketing communication will vary for each customer (Rust and Verhoef 2005). Therefore, these arguments suggest the following:

> *Proposition 1*: The direct effects of economic and relational marketing communication on customers' purchase behavior are heterogeneous.

Long-term Effects of Direct Marketing Communication

Second, we study the long-term effects of marketing communication on customer purchase behavior. Customers' past experience with a firm affect their decision to repurchase from the particular firm (Aflaki and Popescu 2014; Bolton, Lemon, and Bramlett 2006). Especially, customers remember how the firm interacted with them and how much each interaction will be remembered in the customers' mind will significantly vary for each customer. Therefore, in addition to the direct and temporary effect of the marketing communication in period *t* on purchase revenue in period *t* as previously discussed, the marketing efforts can also contribute in creating the latent stock of firm's direct marketing efforts (Leeflang et al. 2009). The latent stock of direct marketing communication up to period *t-1* and the direct marketing communication initiated by the firm in period *t-1* (i.e., the economic and relational marketing communications independently as well as interactively), will have an effect on formulating of the latent stock of marketing efforts in period *t* which will have an effect on customer's purchase revenue in period *t*. Thus:

> *Proposition 2*: Economic and relational marketing communications have a long-term effect on customers' purchase behavior by formulating the latent stock of direct marketing communication.

Uncover Perceived Importance of Economic and Relational Value

Finally, we empirically capture the evolving nature of perceived importance of economic value and relational value. Prior literature noted that various marketing activities lead to different forms of perceptions (Berry 1995; Palmatier, Gopalakrishna, and Houston 2006) and that those perceptions are multi-dimensional (Crosby, Evans, and Cowles 1990). Based on utility theory, individuals respond to an action when it provides additional perceived value. Hence, the two dimensions of perceived importance, whether economic vs. relational direct marketing communication offered by the firm is important to the customer or not, can be inferred from the responsiveness to the particular marketing communication. Further, given the information delivered from the firm, customers cognitively process the information which forms a "perceived importance" (Monroe, Rikala, and Somervuori 2015). Therefore, we believe what the firms offered in the past contribute in formulating perceived importance of economic value and relational value. Additionally, customers update their perceived importance based on their prior perceived importance and experience (i.e., state dependence). Therefore, the perceived importance of economic value (perceived importance of relational value) in period *t* includes the carryover effect of the prior perceived importance of economic value (perceived importance of relational value) in period *t-1* which summarizes the perceived importance of economic value up to period *t-1*. Further, direct marketing communication of the specific value by the firm to a customer in the last period *t-1*(i.e., economic marketing communication) will directly affect the formation of a customer's perceived importance of the specific value (i.e., perceived importance of economic value) in period *t*. Thus:

> *Proposition 3a*: Customers update the perceived importance of economic value based on their prior perceived importance of economic value and the economic marketing communication received.

> *Proposition 3b*: Customers update the perceived importance of relational value based on their prior perceived importance of relational value and the relational marketing communication received.

Then, the customers' perceived importance influence their responsiveness to new information (Bolton, Lemon, and Verhoef 2008). Depending on how customers perceive economic and relational value, customer reactions to new marketing communications can change overtime. Previous empirical research has suggested that there is a greater likelihood of sales when the marketing communications are aligned with customers' needs (Kumar, Venkatesan, and Reinartz 2008). Further, customers use the relevant information received through marketing contacts given the limited time and resources when responding to the new information (Mitra and Golder 2006). Therefore, these arguments suggest the following:

> *Proposition 4a*: The direct impact of economic marketing communication on purchase behavior strengthens when the customers' perceived importance of economic value is higher.

> *Proposition 4b*: The direct impact of relational marketing communication on purchase behavior strengthens when the customers' perceived importance of relational value is higher.

Based the conceptual framework in Figure 1, we illustrate the overview of the empirical analysis in Figure 2. In Stage 1, we describe how the key variables: economic and relational marketing communication are empirically measured using a three-step procedure. The customer-level marketing and transaction data employed in the current study is also described in this stage. In Stage 2, we model the relationship between the direct marketing communication and the customer purchase behavior using the state space model. In Stage 3, we estimate the proposed model using a Bayesian approach. The estimation algorithm and the issues related to estimation such as the identification problem, the marketing endogeneity bias, as well as the validation of the model results are also discussed in this stage. Then in the last stage, we conduct a post-hoc analysis using the model results to find implications for marketing resource reallocation strategies.

[Insert Figure 2 about here]

DATA

The dataset employed for the empirical analyses comes from a Fortune 500 B2B service firm[2] that offers shipping services to business organizations. The firm has presence in every state in the United States and also in other countries. Our data is composed of a representative sample of small to medium sized business clients (i.e., the total number of employees is less than 400 and the annual purchase revenue is less than $200,000 which is defined by the B2B service firm) headquartered in the United States. We use the observation period of January 2011 to December 2014 (i.e., 48 months), during which each customer's purchase history and marketing contact information were recorded. Firm characteristics (e.g., employee size, industry) collected via the focal firm is also available in the dataset.

Since one of the main research objectives is to identify how a customer's perceived importance evolve over time due to the direct marketing communication, we choose a cohort of clients (e.g., buying firms) who started their relationships with the focal firm in December 2010 to January 2011. To account for a possible sample selection bias given that we restrict our sample to customers who started their transactions in the same time period, we randomly

[2] The name of the firm cannot be revealed due to a non-disclosure agreement.

selected two additional samples of 680 customers who made the first transaction in two different time points (i.e., June to July of 2011 and January to February of 2012). Based on the comparison on three variables – the monthly average purchase revenue, monthly average marketing investments, and the employee size – the multivariate analysis of variance (MANOVA) results indicate that there is no significant difference between the three samples (Wilks $\lambda = 0.996$, $F(6,4060) = 1.23$, $p > .10$). Thus, choosing a cohort does not lead to sampling bias in the study.

Key Variables and Measures

The key independent variables in the study are the direct marketing communications focusing on *economic value* vs. *relational value*. Due to the frequency of communications and complexity of transactions in B2B markets, longitudinal data containing information of firm-initiated marketing communication at the customer-level is very rare. The unique feature of this dataset is that we observe the time and the content of customer-level marketing communications that are initiated by the focal firm. Especially, the details on the key message delivered through the interactions with the clients which are initiated by the focal firm's employees are observed in the dataset. Furthermore, the dollar value of each interaction is provided by the focal firm which is based on duration of the interaction, mode of contact, and the contact employee's job classification. It is important to note that direct marketing communication is not bounded by the level of service contracts with different pricing ranges in this study setting. Literature in B2B service industry (e.g., computing, telecommunications, financial services) has mostly focused on the issues in the service contractual settings where the level of firm initiated interactions varies only under different contracts (Bolton, Lemon, and Verhoef 2008). However, the current B2B service firm proactively contacts clients through multiple channels (e.g., email, phone, and in-person) as additional efforts to communicate relational values and discuss information on financial resources the firm can provide with no additional charges.

Measuring economic and relational marketing communication

The key challenge of the research is to identify the economic vs. relational marketing communication from the observed data. The unique feature of the data is that the focal firm's employees who made the contact with the client have qualitatively documented the objective of their interactions as *action comments*. Therefore, we use content analysis to assess the measure of our study which is combined with a rich text analysis of action comments. Content analysis has been frequently employed in marketing literature in various contexts: assessing CEO attention from letters to shareholders (Yadav, Prabhu, and Chandy 2007), gaining insights of firm's orientation from IPO filing documents (Saboo and Grewal 2013) and capturing customers' service experiences from surveys (Kumar et al. 2014). Following the guidelines in the literature, we use a three-step procedure to measure economic and relational marketing communication.

In the first step, we develop an instruction manual for coding the direct marketing interactions and a dictionary to capture the desired construct using the existing literature (Berry 1995; Bolton, Smith, and Wagner 2003; Dwyer, Schurr, and Oh 1987; Gassenheimer, Houston, and Davis 1998; Palmatier, Gopalakrishna, and Houston 2006). The definition of constructs and the dictionary of words belonging to each construct are validated by the senior marketing director at the focal firm. Using prior literature, we offer examples of key words that map onto each construct in Table 2.

[Insert Table 2 about here]

In the second step, we categorize the direct marketing communication as economic vs. relational marketing communication by employing a content analysis (Kassarjian 1977). Using the dictionary of words associated with the two constructs determined in the first step, we computed the frequency of words belonging to each construct from the action comments. We calculate the frequency proportion of words which is the frequency of words belonging to either economic marketing communication (EM) or relational marketing communication (RM) divided by the total words used to describe the core value communicated through direct marketing efforts. Using the frequency proportion of words belonging to either economic vs. relational marketing communication, we categorize each contact into two constructs. For example, a total number of 100 words are used in comments describing the direct marketing efforts. We find that the frequency of words belonging to economic marketing communication is 30 (i.e., the frequency proportion of EM is 0.3) and the frequency of words belonging to relational marketing communication is 5 (i.e., the frequency proportion of RM is 0.05). Then, we categorize the direct marketing effort as economic marketing communication as the frequency proportion of EM is higher than the frequency proportion of RM. However, hybrid messages do exist in the dataset. Therefore, when the frequency proportion of the words belonging to two constructs are similar (i.e., ±10%), we code the contact to be both economic and relational marketing communication. A total of 111,710 contacts are coded which consist 31.09 words observed on average in each contact.

To verify, the results are compared with the categorization by the *action type* which is the focal firm's internal categorization of direct marketing communications. For example, when the action type is indicated as "post sales - regular checkup," we compare the categorization from the content analysis in the first step to find out whether the particular direct marketing effort is coded "relational marketing communication". The mismatches were computed after the iterations and we made changes to the initial dictionary accordingly. However, we do not solely rely on the action type to categorize the direct marketing communication as there are hybrid messages and 15% of the comments are categorized as “others”. Further, we randomly select one hundred action comments from the data and ask ten experts in the area to categorize the marketing communication. Fleiss Kappa index for the reliability across the ten raters and the coded results from the second phase was 0.81 ($z = 53.62$, $p < .001$), indicating a reasonable level of agreement and a satisfying inter-rater reliability.

There are various ways to operationalize the direct marketing communication. Yet, it is important to account for the quality of the marketing interaction since it has a significant influence on financial and relational outcomes. Especially the quality of the interaction can vary by the expertise of the firm’s employees (Mitręga and Katrichis 2010). Thus, the marketing communication in dollar value accounts for the information on the employee’s job classification, mode of contact, and duration of the interactions which can infer the quality of interactions. Furthermore, irregular spikes can be observed when a pure frequency measure is used that lacks information about the intensiveness of the marketing communication. Therefore, in the third step, we operationalize the economic and relational marketing communication (i.e., $\mathrm{EM}_{\mathrm{it}}$ and $\mathrm{RM}_{\mathrm{it}}$ in the following model section) as a dollar value (i.e., how much the firm invested) to deliver the particular type of value to each client in a month.[3] When the contact is coded as delivering both types of value, the dollar value of the marketing efforts were split into half indicating that the particular marketing efforts focus on both economic and relational value.

Other variables

We use purchase revenue in a month as the dependent variable representing a customer’s purchase behavior which reflects that client’s needs. Since the purchase of the service is quite

[3] Pairwise correlations of the frequency proportion of words and the current operationalization of direct marketing communication (i.e., dollar value) show high correlation coefficients between the two measures for both economic and relational marketing communication (i.e., $\rho=0.71$ and 0.67).

regular and the firm indulges in building close relationships with the customer in a B2B setting on a frequent basis (Luo and Kumar 2013), we use monthly time intervals to utilize the rich information and also capture the dynamics in purchase behavior. For control variables, we use exchange characteristics in the past such as the cumulative average purchase revenue until the last month (i.e., t-1), the dormancy of transactions (i.e., whether (1) or not (0) the customer made a purchase more than 6 months ago), the cumulative average cross-buy level (i.e., the number of different services used) until the last month, and the cumulative average price per unit until the last month. Especially, we account for the actual discounts provided to each customer by including cumulative average price per unit as one of the control variables to find the direct impact of economic marketing communication on customer purchase behavior.[4] Additionally, to account for the observed heterogeneity, we use the employee size and six industry dummies which include high-tech, health care, manufacturing, etc.

Descriptive Statistics

We present the summary statistics of the purchase information, the marketing investment history, and employee size of the 675 clients during the observation period in Table 3. The clients in our sample on an average purchased in 40.7 months during the span of 48 months and the average purchase revenue per month is $1,227.9. Within each client, the average standard deviation of the purchase revenue is 761.6 showing that there is high variance in the purchase revenue indicating that clients constantly make decisions to buy more or less in each time period. The total number of direct marketing contacts initiated by the firm at the monthly level is 8.5 times and the monthly average direct marketing investment for a client is $36.2. On an average, the firm spends $17.5 in economic marketing communication and $18.7 in relational marketing

[4] Price discounts are offered by the volume of order at the firm.

communication. The average employee size of clients is 14.3. The pairwise correlation coefficients of the continuous key variables used for the study are shown in Table 4.

[Insert Table 3 about here]

[Insert Table 4 about here]

Model Free Evidence

Before introducing the formal model, we present a model free evidence of the effects of direct marketing communication on customer purchase behavior. Consider the case of 2 actual clients of a firm used in the study over an observation period of 48 months as illustrated in Figure 3. On an average, the firm spends a similar amount of marketing investments on two customers, Customers 1 and 2. However, as shown in Figure 3, customers generate different levels of revenue in different time points. We can observe that direct marketing communications have contemporaneous as well as lagged effects on purchase revenue. Yet, from this figure, it is hard to find which type of direct marketing communication is more effective in each time given the customer's past experience with the firm. Thus, to understand the extent of each direct marketing communication on customer purchase behavior, proposing a model which accounts for the customer heterogeneity and long-term effects of marketing is crucial.

[Insert Figure 3 about here]

MODEL

A key challenge in specifying our model is that the customers can keep on updating their perceived importance of the values offered and also store the memory of firm initiated contacts which are unobserved, heterogeneous, and changes overtime based on the prior perceived importance and experience. To estimate varying parameters over time and also account for the cross-sectional heterogeneity, we use the state space modeling approach. There are two benefits of using the state space model. One of the major advantages of using the state space model is its ability to estimate the unobservable component, *state*, which is developed over time with a set of observations (Durbin and Koopman 2012). Thus, we model the (i) dynamics of customers' latent information stock of direct marketing communication and (ii) the perceived importance of economic and relational value influenced by direct marketing communication using the state space modeling approach. Secondly, the desirable property of the state space model is that the observation and state equations are estimated simultaneously instead of two separate stages (Leeflang et al. 2009). Therefore, our model consists of two equations: the observation equation and the state equation. The observation equation specifies a continuous observation of purchase revenues, conditional on the customers' decision to purchase which is affected by the dynamic responses to firm's communication efforts. The state equation describes the nature of dynamics of parameters in observation equations.

Observation Equation

Following the key drivers of purchase revenue as mentioned in the earlier section, we apply the Type I Tobit model. Given that the data are censored at 0 for the no purchase occasion, the data are not distributed normally. Therefore, we use the Type I Tobit model which augments the data by drawing values from a truncated normal distribution to remove any bias in the estimation procedure. We have specified the observation equation as follows:

(1) $$\mathrm{Y_{it}}^* = \mathrm{I_{it}} + \alpha_{it}\mathrm{EM_{it}} + \beta_{it}\mathrm{RM_{it}} + \lambda \mathrm{C_{it-1}} + \zeta \mathrm{F_i} + \varepsilon_{it}$$

$$\mathrm{Y_{it}} = \begin{cases} \mathrm{Y_{it}}^* & \text{if} \quad \mathrm{Y_{it}}^* > 0 \\ 0 & \text{if} \quad \mathrm{Y_{it}}^* \leq 0 \end{cases}$$

where,
$\mathrm{Y_{it}^*}$= the latent purchase revenue variable of customer i in time period t
$\mathrm{Y_{it}}$ = the observed purchase revenue generated by customer i in time period t
$\mathrm{I_{it}}$= the intercept for customer i in time period t
$\mathrm{EM_{it}}$ = economic marketing communication (EM) to customer i in time period t

RM_{it} = relational marketing communication (RM) to customer i in time period t
C_{it-1} = matrix of control variables of customer i in time period t-1
F_i = column vector of customer-specific variables of customer i
α_{it} = responses to EM of customer i in time period t
β_{it}= responses to RM of customer i in time period t
λ = parameters of control variables
ζ = parameters of customer-specific variables
ε_{it} = random errors

We model each customer's total expenditures. We model the direct effects of economic marketing communication (EM) and relational marketing communication (RM) on customer purchase. I_{it} is the customer-specific time-varying intercept. The dynamic parameters, α_{it} and β_{it}, capture the customers' sensitivity towards these firm initiated marketing communications. The matrix of control variables (C_{it-1}) includes the customer-level information on the past transactions (e.g., cumulative average purchase revenue, last transaction time, cumulative average cross-buy level, and cumulative average price) that affects the purchase revenue of customer i in time period t. Firm characteristics (F_i) such as employee size and industry dummies are used to account for observed heterogeneity. The random error, ε_{it} has normal distribution with mean 0 variance ${\sigma^2}_{\varepsilon}$, capturing the information unobserved by the researcher.

State Equations

A core contention of our research is to understand the dynamic effects of direct marketing communication on customer purchase behavior. The key aspects of the dynamic effects are: (i) how the firm's marketing efforts contribute in creating the latent information stock and (ii) how the direct effects of marketing communication on purchase behavior are moderated by the customers' perceived importance of economic and relational value. To test this conjecture, we specify the intercept as well as the responses to two types of marketing communications, economic marketing communication (EM) and relational marketing communication (RM), as state equations. The state equations describe how the intercept (I_{it}) and marketing response parameters (α_{it} and β_{it}) in the observation equation evolve over time.

Based on the conceptual framework shown in the earlier section, we study the long-term effects of marketing efforts on customer purchase behavior by capturing each customer's tendency to accumulate the past information in a latent stock. Similar to how past online communications or advertisements contribute to a stock of corporate goodwill (Sonnier, McAlister, and Rutz 2011; Sriram, Chintagunta, and Neelamegham 2006), we capture the indirect effects of direct marketing communication by creating a state-dependent stock. Therefore, we construct the customer-specific time-varying intercept (I_{it}) as the latent stock of direct marketing communication (EM_{it-1}, RM_{it-1}). We include the time invariant component (δ_{0i}) to capture the unobserved heterogeneity in the purchase revenue and also include the interaction of direct marketing communication ($EM_{it-1} * RM_{it-1}$) to study the synergy effect.

Also, as customers respond to an action when they perceive the provided value to be important them, we interpret the response parameters (i.e., α_{it} and β_{it}) as our perceived importance measures. We explain the sensitivity trend of different marketing communications by the time invariant component (θ_{0i}, γ_{0i}), and the time variant component. The time variant component can be explained by the notion that the perceived importance changes over time due to the specific marketing communication in the past (EM_{it-1}, RM_{it-1}) and the past perceived importance (α_{it-1}, β_{it-1}). Such a model formulation is consistent with the studies on the long-term effect of marketing on consumer preferences (Sriram, Chintagunta, and Neelamegham 2006). Therefore, we specify the state equations as follows:

(2) $$I_{it} = \delta_{0i} + \delta_{1i} I_{it-1} + \delta_2 EM_{it-1} + \delta_3 RM_{it-1} + \delta_4 EM_{it-1} * RM_{it-1} + \omega_{it}$$

(3) $$\alpha_{it} = \theta_{0i} + \theta_{1i} \alpha_{it-1} + \theta_2 EM_{it-1} + \eta_{it}$$

(4) $$\beta_{it} = \gamma_{0i} + \gamma_{1i} \beta_{it-1} + \gamma_2 RM_{it-1} + \nu_{it}$$

where,
I_{it-1}= the latent stock of direct marketing communication of customer i in time period t-1
α_{it-1}= perceived importance of economic value of customer i in time period t-1
β_{it-1} = perceived importance of relational value of customer i in time period t-1
δ_{0i}, θ_{0i}, γ_{0i} = customer i specific steady state mean
EM_{it-1} = economic marketing efforts to customer i in time period t-1
RM_{it-1} = relational marketing efforts to customer i in time period t-1
δ_{1i}, θ_{1i}, γ_{1i} = decay rates of the states of customer i
δ_2, δ_3, δ_4, θ_2, γ_2 = parameters of marketing efforts in time period t-1
ω_{it}, η_{it}, ν_{it}= random errors

The initial states are assumed to follow a normal distribution (i.e., $I_{i1} \sim N(mi_1, pi_1)$, $\alpha_{i1} \sim N(ma_1, pa_1)$, and $\beta_{i1} \sim N(mb_1, pb_1)$). We use a normal distribution to model customer heterogeneity ($\delta_{0i} \sim N(\overline{\delta_0}, V_{\delta_0})$, $\theta_{0i} \sim N(\overline{\theta_0}, V_{\theta_0})$, and $\gamma_{0i} \sim N(\overline{\gamma_0}, V_{\gamma_0})$). Since clients can weigh the past latent stock of direct marketing communication and past perceived importance differently, we use the customer-specific autoregressive parameters (δ_{1i}, θ_{1i}, and γ_{1i}). The carryover rates range from 0 to 1 with 0 implying the effects of past on current response is the lowest, whereas 1 implying the effects of past are most enduring (Ataman, Van Heerde, and Mela 2010). We employ the inverse-logit transformation to constrain the parameters.[5] We estimate the parameters for past marketing efforts affecting the accumulation of latent stock of direct marketing communication (δ_2, δ_3, and δ_4). Further, the parameters for past marketing efforts affecting the sensitivity to the new marketing efforts (θ_2 and γ_2) are estimated. We allow the evolution process to be probabilistic by including the random errors ω_{it}, η_{it}, and ν_{it} which has a normal distribution with mean 0 and variance $\sigma^2{}_{\omega}$, $\sigma^2{}_{\eta}$, and $\sigma^2{}_{\nu}$.

[5] We parameterize the autoregressive parameters, δ_{1i}, θ_{1i}, and γ_{1i} using the inverse-logit transformation (e.g., $\exp(\widetilde{\delta_{1i}})/(1+\exp(\widetilde{\delta_{1i}}))$ where $\widetilde{\delta_{1i}}$, $\widetilde{\theta_{1i}}$, and $\widetilde{\gamma_{1i}}$ are unconstrained parameters with the following distribution: $\widetilde{\delta_{1i}} \sim N(\overline{\delta_1}, V_{\delta_1})$, $\widetilde{\theta_{1i}} \sim N(\overline{\theta_1}, V_{\theta_1})$, and $\widetilde{\gamma_{1i}} \sim N(\overline{\gamma_1}, V_{\gamma_1})$.

MODEL ESTIMATION

We estimate the latent dependent variable, Y_{it}^*, using data augmentation which has been widely adapted for use in Tobit models (Chib 1992). When the dependent variable is not observed (i.e., $Y_{it} = 0$), the latent dependent variable is imputed from a truncated normal distribution so that $Y_{it}^* \leq 0$. We combine the data augmentation strategy and the Gibbs sampler methods to estimate equations (1)-(4). A key challenge in estimating our proposed model framework is to estimate the unobserved value of latent stock of direct marketing communication (I_{it}) and perceived importance (α_{it} and β_{it}) which includes the cross-sectional heterogeneity (δ_{0i}, θ_{0i}, and γ_{0i}). We use Kalman filtering estimation (a commonly used method to estimate standard state space models) is used to estimate the continuous unobserved state variables (Sriram, Chintagunta, and Neelamegham 2006; Zhao, Zhao, and Song 2009). We provide detailed descriptions of the priors and the estimation algorithm in the **Appendix A**. By generating 50,000 iterations and discarding first 25,000 iterations as the burn-in period, we use a total of 25,000 iterations for the model inference. We also use every 10th draw for inference to reduce autocorrelation in the Gibbs draws. The Gelman-Rubin diagnostic which is widely used to check the model convergence shows that all variables in the model have scale reduction factors that are less than 1.1 suggesting an adequate model convergence (Gelman and Rubin 1992). In the following section, we discuss some of the issues related to the estimation of the proposed model.

Model Identification

Given the structure of the model, we believe it is important to provide some intuition regarding the identification of the model parameters. To identify the dynamics, we first exploit the changes in customer purchase behavior. The direct marketing communication influences clients to buy more or less from the firm. Clients can shift to competitors as the treatment they are getting from the focal firm is not valuable (e.g., benefits offered from the focal firm are not matching). However, the changes in customer purchase behavior can also be driven due to changes in need (Kumar et al. 2011). Although we have limited information on the competitor's actions and customer purchase behavior with the competitors to tease out these differences, we partially control for that by accounting for the customer's past purchase behavior and also by acknowledging that the service provided by the focal firm is a frequently purchased and one of the most critical services for all the customers. Empirically, we find enough cross-sectional variation (i.e., the average standard deviation of the purchase revenue comparing clients is 1315.85 during the observation periods) as well as temporal variation (i.e., the average standard deviation of the purchase revenue is 761.6 for all clients) in the purchase revenue to understand the changes in customer's responses to firm actions.

Another argument here is how we can identify the short (direct) and long (indirect) term effects of direct marketing communication. Again, we find enough cross-sectional variation as well as temporal variation in the economic and relational marketing communication which facilitates the identification of parameters. We can identify the direct effects of marketing by studying how the variations in marketing dollars result in changes in customer purchase revenue. The indirect effects of marketing (e.g., parameters in the state equations) is identified as the direct effects (i.e., α_{it} and β_{it}) can be apportioned between direct and indirect effects by using the state equations which have similar formats as time-series equations to understand the marketing response parameters. Based on the conceptual framework, we also use an exclusive variable (e.g., only include past economic marketing communication to understand response to the current economic marketing communication) to identify the parameters. Further, to ensure empirical identification, we estimate the model using simulated data which mimic our actual data and the results reveal that the model and the estimation procedure can recover the parameters with a reasonable level of accuracy (see **Appendix B** for details).

Correcting for Endogeneity Bias

A potential concern in the proposed model framework is that the error term in the observation Equation (1) is likely to be correlated with economic marketing communication (EM) and relational marketing communication (RM). As known, measurement error, omitted variable bias, and simultaneity can drive potential endogeneity bias. Thus, we account for endogeneity of marketing communication through a control function approach (Petrin and Train 2010) by adding unobserved factors that are correlated with EM and RM but are not correlated with the purchase revenue. We check the instrument relevance of whether our chosen instrumental variables actually predict the marketing investments made. Conceptually, we make a case that the firm's marketing communications are typically allocated based on the budgeting strategy of the marketing managers (Petersen and Kumar 2014). We use the total marketing budget and average marketing investment per contact on economic marketing communication and relational marketing communication in the previous quarter to customers who are in the same industry or to customers who are headquartered in the same geographic location as the instruments. Further, the growth in purchase revenue for each customer from the previous quarter is used as an instrument to account for the endogeneity of marketing communication.

When picking the instrumental variables in the study, the instrument relevance as well as the exclusion restriction (i.e., be uncorrelated with the omitted variables) should be checked. The customer-level marketing interventions of competing firms and each salesperson at the selling-firm initiating direct marketing communication based on their knowledge of the customer's sensitivity to these efforts can be the major categories of omitted variables. Since the focal firm does not observe what kind of direct marketing communications are initiated by the competing firms, it is unlikely that the instruments will correlate with the omitted variables, thereby meeting the exclusion criterion. After discussing with the managers at the focal firm, we also acknowledge that the focal firm has the CRM software to enforce the firm-level strategy and to minimize each salesperson's decision in delivering messages to the customers, confirming that there is the low likelihood of instrumental variables being correlated with the omitted variables. Therefore, we regress the endogenous variables (i.e., EM and RM) on instruments and we introduce the two residuals as the additional regressors in Equation (1) and maximize the likelihood function. We report the estimates of regressing EM and RM on instruments in **Appendix C**.

RESULTS

We present the results from the model estimation in Table 5. The posterior mean and the standard error of the estimates are shown here.

[Insert Table 5 about here]

We first discuss the estimates pertaining to the state equations. For the intercept which represent the latent stock of direct marketing communication (I_{it}), we find that there is a significant customer-level shifter as shown in the estimates of the steady state mean ($\overline{\delta_0}$ = 4.36). We also find that there is an unobserved across customer heterogeneity in the purchase revenue from the estimates of the variance (V_{δ_0}= 0.77) which is also shown in Figure 4A. The posterior mean estimates of the carryover parameter ($\overline{\delta_1}$) is 0.61. Yet, given that we parameterize the autoregressive components using the inverse-logit transformation, the parameterized carryover estimates of the latent stock variable is shown in Figure 4D. For the contemporaneous effects, we find that economic marketing communication (EM) as well as relational marketing communication (RM) have positive effects on purchase revenue (δ_2=0.44, δ_3 =0.57). Further, the interaction effect of EM and RM is also shown to have a positive effect on purchase revenue (δ_4=0.21). The model result is consistent with the literature that the marketing efforts can contribute in creating the latent stock of firm's direct marketing efforts (Leeflang et al. 2009).

[Insert Figure 4 about here]

We also report the estimates of the mean and the variance of customer-specific steady state mean (θ_{0i}, γ_{0i}) in how customers perceive the values communicated through the different direct marketing efforts. The time invariant components of the perceived importance of economic value (EV) and relational value (RV) have positive posterior mean. The result indicates that both economic marketing communication (EM) and relational marketing communication (RM) on average for all customers have positive effects on the purchase revenue. Yet, the posterior mean obtained for the time invariant component of the perceived importance of economic value ($\overline{\theta_0}$) is 0.61 whereas the posterior mean obtained for the time invariant component of the perceived importance of relational value ($\overline{\gamma_0}$) is 0.44. The mean comparison result reveals a significant difference in time-invariant components of the perceived importance of economic and relational value ($F(1,1349)=22.65$, $p<.01$)). The heterogeneity of customer's mean level perceived importance towards two types of value is illustrated in Figures 4B and 4C. The horizontal axis is the size of the customer-level parameter estimates related to EM and RM (θ_{0i}, γ_{0i}), and the vertical axis represents the frequency with which that level of steady state mean is estimated. We can see that our model reveals considerable customer heterogeneity of steady state mean which is also shown in the model result (V_{θ_0}=0.56, V_{γ_0}=0.70). Contrary to most previous studies focusing on the positive relationship between marketing efforts and customer dependence (or customer loyalty), we find that some customers are actually more suspicious with regard to what they received given negative parameters for some people (Mitręga and Katrichis 2010).

Regarding the time-variant component, we find the evidence of dynamics in marketing responses. The parameter θ_{1i} and γ_{1i} captures the carryover rate of the perceived importance of economic and relational value. The results reveal that the mean of carryover parameters are significantly different from zero which is consistent with the notion that the perceived importance, the interpretation of the weight of the values offered, are an enduring construct (Puccinelli et al. 2009). The results also indicate that there is a positive moderating effect of a customer's perceived importance in the previous period (t-1) on the effect of current marketing on purchase behavior which is consistent with the findings from the prior research that the customers' prior opinions influence responsiveness to new information (Bolton, Lemon, and Verhoef 2008). The posterior mean carryover rate of perceived importance of economic value ($\overline{\theta_1}$) is 0.55 and posterior mean carryover rate of relational value ($\overline{\gamma_1}$) is 0.64. Given that we parameterize the autoregressive components using the inverse-logit transformation, we show the parameterized carryover estimates of the perceived importance of economic value and relational value in Figures 4E and 4F. The figures show considerable heterogeneity of carryover parameters as also shown in the model results (V_{θ_1}=0.38, V_{γ_1}=0.33). Especially, the carryover rates of perceived importance of relational value is more skewed towards 1 than the perceived importance of economic value revealing longer lived effects of relational marketing communication than economic marketing communication. The mean comparison result reveals a significant difference in the carryover effects of the perceived importance of economic and relational value ($F(1,1349)=22.41$, $p<.01$)). The finding is consistent with Dwyer, Schurr, and Oh (1987) that relational exchanges lasts longer in duration.

Additionally, we find that the effect of EM in the previous period has a positive effect on perceived importance of economic value (θ_2=0.26). The effect of RM in the previous period is also found to have a positive effect on perceived importance of relational value (γ_2=0.28). The result shows that the marketing communication efforts delivering the specific value have significant effect on the corresponding perceived importance due to the degree of fitness. Finally, our estimates of the perceived importance at the initial period are also significantly different from zero.

To account for the observed heterogeneity we use the past exchange characteristics and customer specific variables (i.e., firm characteristics) in the model. The results reveal that consistent level of purchases made in the past (i.e., one month lag of cumulative average purchase revenue) has a positive impact on current purchase revenue. The dormancy in purchase (i.e., last purchase in over 6 months ago) has a negative impact on current purchase revenue indicating the lower likelihood of purchase after a long period of inactivity. The cumulative average cross-buy level (e.g., number of different services used) in the last month which indicates the customer's loyalty level has positive impact on current purchase level. The cumulative average price per unit in the last month which indicates the price level the customers are in has a negative impact on current purchase revenue.

We also find that some of the industry dummies[6] such as industry 1, 2, 3, and 6 have significant impact on the purchase revenue. The employee size has significant positive impact on current purchase revenue indicating the bigger the firm size the higher the purchase revenue. Further, the endogeneity correction terms for both economic marketing communication (EM)

[6] For reasons of confidentiality, we cannot reveal the description of each industry dummy.

and relational marketing communication (RM) have negative signs suggesting that the positive effects of EM and RM are lower for the low level of EM and RM.

Model Comparison

We compare the proposed model with four benchmark models to assess the validity of our model which accounts for the customer heterogeneity and dynamics in parameters. The four benchmark models are (1) a base model (i.e., Type 1 Tobit model with no heterogeneity and dynamics), (2) a model which only account for heterogeneity (i.e., equation (1) is defined as $\mathrm{Y_{it}}^{*} = \mathrm{I_i} + \alpha_i \mathrm{EM_{it}} + \beta_i \mathrm{RM_{it}} + \lambda \mathrm{C_{it-1}} + \zeta \mathrm{F_i} + \varepsilon_{it}$), (3) a model which only account for dynamics (i.e., equation (1) is defined as $\mathrm{Y_{it}}^{*} = \mathrm{I_t} + \alpha_t \mathrm{EM_{it}} + \beta_t \mathrm{RM_{it}} + \lambda \mathrm{C_{it-1}} + \zeta \mathrm{F_i} + \varepsilon_{it}$), and (4) a state space model with no contemporaneous marketing efforts (i.e., equations (2) to (4) are defined as (e.g., $\mathrm{S_{it}} = \mathrm{d_{0i}} + \mathrm{d_{1i}} \mathrm{S_{it-1}} + \mathrm{v_{it}}$) (see Table 6). We use the hit ratio and the Relative Absolute Error (RAE) to compare the performance of the proposed model with benchmark models (Luo and Kumar 2013). RAE is defined as the mean absolute error of a proposed model divided by the mean absolute error of the benchmark model (Armstrong, Morwitz, and Kumar 2000). We also randomly selected a sample of 500 customers who started their transactions with the firm in different time period (June to July of 2011) to compute the out-of-sample fit.

[Insert Table 6 about here]

As Table 6 indicates, the proposed model gives the best fit in terms of the hit ratio and the RAE since the hit ratio is the highest and RAE values of the benchmark models are less than 1 indicating that the mean absolute error of the proposed model has the lowest value compared to the mean absolute error of the benchmark models. When customer heterogeneity and the time-varying parameters are not taken into account (benchmark model 1), we find that the model performance significantly drops to 79% for the hit ratio and RAE of 0.14. When customer heterogeneity is considered (benchmark model 2), the model performance improves to 84% for the hit ratio and 0.34 for RAE. When we account for the dynamics in time (benchmark model 3), we find that the model performance slightly improves again to 86% for the hit ratio and 0.42 for RAE. When considering the state dependence of the purchase behavior and the effects of marketing efforts (benchmark model 4), the model performance shows the hit ratio of 88% and RAE of 0.83. Yet, the proposed model yields the best model performance compared benchmark models. We also find that out-of-sample and in-sample fits give similar results.

We also coarsely aggregate the data (i.e., quarterly) to evaluate the robustness of the results when an alternative level of aggregation is used and also to find out the consistency in the model results when the Tobit model is not used. We find that the direction and the relative magnitude of the estimated parameters are similar to the model results using monthly data. Further, we run the additional robustness analysis on two different cohorts (i.e., customers who started their transactions in June to July of 2011 or January to February of 2012) and obtained qualitatively similar results.

DISCUSSION

Internal Validation of Model Results

To ensure that the model captures the proposed latent constructs, the perceived importance of economic and relational value, we conduct an additional analysis by comparing the estimated perceived importance to the self-reported measures for a different set of customers. Survey data for 256 customers were collected from the focal firm asking questions such as the overall satisfaction and repurchase intention. We use a two-step procedure to conduct the internal validation. First, we estimate all of the parameters using our modeling framework and uncovered the average level of perceived importance of economic and relational value in the 48 months observation period. Second, we compare the average level of perceived importance of economic and relational value to the two survey items (i.e., “1.Would you seek for more competitive pricing? (1 = least likely, 10 = most likely)”, “2. How would you rate the service experience with the employee? (1 = highly unsatisfied, 10 = highly satisfied)”). We find that the pairwise correlations between the survey items and the average perceived importance of economic value is higher for the first item (reversely coded; ρ=0.63 (p<.01)) than the second item (ρ=0.22 (p<.01)). Comparably, we find the pairwise correlations between the survey items and the average perceived importance of relational value is higher for the second item (ρ=0.69 (p<.01)) than the first item (reversely coded; ρ=0.35 (p<.01)). We find the result to be consistent with our definition of the two constructs that when the perceived importance of economic value is higher, customers are more satisfied with economic value offered and less likely to look for additional option (e.g., lower the value for survey item 1). On the other hand, we find that when the perceived importance of relational value is higher, customers are more satisfied with the services offered by the firm employees.

Relative Importance of Marketing Efforts

What is the relative importance of two types of marketing efforts, economic and relational marketing efforts to each customer? How does the response to marketing efforts differ by the customers’ characteristics? As discussed earlier, customers formulate their perceptions after considering the degree of fit given their needs (Steenkamp 1990). To find out the customer level differences in their response to the firm’s marketing communication efforts, we conduct a post-hoc analysis of the model parameter estimates shown in Table 4. We calculate the overall average of customers’ perceived importance economic and relational value (average of α_{it} and β_{it} in equation (1)) during the observation periods and construct a 2 by 2 matrix. To qualify as a customer with high vs. low level of perceived importance of economic and relational value, we take top 30% and bottom 30% of customers after rank ordering the perceived importance level and randomly sampled customers to have an equal number of customers in each segment (i.e., 85 customers in each segment).

As shown in Figure 5, we find that larger firms tend to value relational benefits more than the economic benefits. Customers with higher purchase revenue value both types of direct marketing communication compared to the firms with smaller purchase revenues. Interestingly, firms that spend relatively higher purchase revenue have stronger perceived of economic value than relational value. Comparing the two variables: the employee size and the purchase revenue per month, the multivariate analysis of variance (MANOVA) results indicate that there is a significant difference among the four segments (Wilks $\lambda = 0.95$, $F(6,670) = 2.73$, $p < .01$). Further, looking at the industry segmentation, we find that customers belonging to industry 1 and 3 have higher perceived importance of the economic value whereas customers belonging industry 5 and 6 have higher perceived importance of the relational value. Further, we find that customers belonging to industry 4 are more responsive to both economic and relational marketing communications. The results are useful to understand the observed heterogeneity and selectively target customers with specific firm characteristics as opposed to a random selection of customers when the longitudinal data of transaction and marketing investments are unavailable for all customers.

[Insert Figure 5 about here]

Quantifying the Effectiveness of Differentiated Marketing

Then, to what extent can firms increase the effectiveness of their marketing communication efforts by selectively targeting (or not targeting) customers on the basis of their perceived importance for different values? Can firms shift their marketing investments focusing on one value to another based on the historic responsiveness to marketing efforts? Each customer will have their own priority before receiving any direct marketing communication from the focal firm. Yet, depending how the focal firm is continuously interacting with the customers and how the customers are interpreting the benefits offered, the customer's purchase decision can be affected. Therefore, we quantify the benefit of considering the customers' perceived importance in the context of reallocating marketing resources within the existing customers of the firm with the objective of increasing the purchase revenue. We quantify this in the context of (a) reallocating marketing resources *within* customers based on their level of perceived importance and (b) reallocating marketing resources *within* customers and *over time* based on their level of perceived importance.

<u>Changing the levels of EM and RM within customers</u>

Since customers value two types of marketing communication differently, we demonstrate the gain in purchase revenue by reallocating marketing resources *within* customers based on their level of perceived importance. For example, when the average perceived importance of economic value (EV) is higher than perceived importance of relational value (RV), we shift 20% of the marketing investments (similar in $ amount) from relational marketing communication (RM) to economic marketing communication (EM). Whereas, when the average perceived importance of relational value (RV) is higher than perceived importance of economic value (EV), we shift 20% of the marketing investments (similar in $ amount) from economic marketing communication (EM) to relational marketing communication (RM).

To find out the effects, we apply the parameter estimates of Table 4 to simulate the change in purchase revenue corresponding to the shift in marketing dollars from economic marketing communication to relational marketing communication, and vice versa. We find that when the marketing investments are reallocated based on the parameters of perceived importance of economic and relational value that we estimated, the total purchase revenue increase by 3.8% (about 1.1 million in dollars) over the observation period. These results underscore the importance of gaining customer-level insights and hence implementing customer-level marketing programs to improve the efficiency and effectiveness of firm's marketing resources.

Changing the levels of EM and RM within customers and over time

To find out the effects of leveraging the dynamic model, we conduct a what-if simulation study to test how much revenue the firm can generate by allocating the marketing resources based on the changes in customers' perceived importance. By using the average perceived importance level for each customer in each year, we shift EM and RM by different percentage level to maximize the overall purchase revenue. For example, when the average perceived importance of economic value (EV) is higher than the average perceived importance of relational value (RV) in year 1 for customer A, we reallocate the marketing investments (similar in $ amount) from relational marketing communication (RM) to economic marketing communication (EM) by the level which maximize the purchase revenue in that year. Whereas, when the average perceived importance of relational value (RV) is higher than perceived importance of economic value (EV) in year 2 for customer A, we reallocate the marketing investments (similar in $ amount) from economic marketing communication (EM) to relational marketing communication (RM) by the level which maximize the purchase revenue in year 2.

Each customer develops the relationship with the firm in a different way. Some customers prefer to build the personal and social relationship (i.e., respond to RM) first and then prefer to discuss the financial benefits (i.e., respond to EM) whereas others prefer to receive economic marketing communication first and then constantly receive relational marketing communication only in the later period. Consequently, by re-allocating the marketing resources for each customer at each time period (i.e., year) given the changing level of perceived importance of economic and relational value, we find that the total purchase revenue can increase by 8.8% (about 2.6 million in dollars) over the observation period. What this indicates is that firms can improve the effectiveness of marketing by utilizing the dynamic model which caters each client's preference. Hence, when firms understand the changes in a customer's responses to firm's action given that the past marketing efforts can formulate perceived importance, more effective marketing resource allocation strategies can be implemented.

IMPLICATIONS

Contribution to the Literature

The potential contributions of this study to the marketing literature are threefold. First, the study empirically identifies the effects of marketing communication in terms of economic and relational values which help firms invoke the right kind of marketing messages. Second, by examining the dynamic effects of economic and relational marketing communications on purchase behavior in a single model, we are able to propose a more effective marketing communication strategy. Third, to the best of our knowledge, this is the first study to empirically quantify the perceived importance of economic and relational value offered using only the transaction data.

From a theoretical perspective, the study builds on extant relationship marketing literature through quantifying the dynamic multi-dimensional perceived importance triggered by a firm initiated marketing communication in the B2B context (Zhang, Netzer, and Ansari 2014). Furthermore, the study overcomes the shortcomings of previous service literature by explicitly studying the customer's dynamic responses that can be measured in purchases as well as perceived importance of economic and relational value in the B2B context (Rust and Huang 2014). From a methodological perspective, the proposed modeling framework integrates the content analysis, customer heterogeneity, the latent stock of information as well as a customer's perceived importance updating process, when modeling the customer's purchase behavior.

Contribution to Practice

This study offers important *managerial implications* for B2B firms, to maximize the financial performance while suggesting marketing resource allocation strategies over time. Specifically, the current study uses customer analytics, readily available to most B2B firms, to better understand customer purchase behavior by uncovering the evolution of perceptions. Given that the effectiveness of economic and relational marketing communications change over time, managers can update their resource allocation strategy to better align with the customer's preferences. Furthermore, by identifying the types of customers who are more sensitive to one interaction over the other, managers can segment and target potential customers and also improve customer relationships by catering to their needs. Because economic and relational marketing communications provide different long-term financial returns, marketers can use the proposed model to optimally allocate a given marketing budget across two types of marketing communications after considering a client's perceived importance.

CONCLUSION & FUTURE DIRECTIONS

The methodology discussed in this study is applicable for firms when longitudinal data of firm initiated marketing communication exist. Another potential limitation of this study is that we do not have proprietary customer databases of competing firms. Therefore, while we do know the marketing information and purchase behavior of each customer at the firm included in this research, we do not have data on the customer's purchase behavior and the marketing offers made from competing firms. This limitation is hard to overcome because acquiring customer level purchase and marketing data of all possible firms where customers are likely to interact is difficult. However, this paper presents an excellent opportunity for future research studies to conduct a multi-firm customer level study (perhaps using syndicated data providers) to analyze how customers perceive values offered by various firms differently and make purchase decisions.

Further research can also consider the synergy effects of two types of marketing communication efforts discussed in the current study and employ a dynamic structural model to recommend optimal marketing resource allocation model (Sridhar et al. 2011). Specifically, the long-term cost information on the economic marketing communication efforts (e.g., actual discounts offered from the firm) will allow the firm to capture the overall cost of marketing investments and allocate the right type of marketing resources and maximize the firm's future profit. Further, employing richer customer level mind-set datasets collected over time will allow managers to empirically validate the change in the customer's preference levels (e.g., satisfaction, attitude). Although the current study is constrained in the B2B context as the relational marketing communications are more prevalent and critical in the B2B markets, the conceptual framework and model can be applied in the B2C context.

In conclusion, this is the first empirical study that models the dynamic effects of two types of marketing communication efforts on a customer's purchase behavior. The findings of this research along with the associated managerial implications are directed to enable marketers to expand their influence in the organization on enhancing the firm's overall performance.

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TABLES AND FIGURES

Table 1. Selected Studies in B2B Context Studying Economic and Relational Marketing Efforts

Studies	Focus on Economic Mkt.*	Focus on Relational Mkt.	Content of Mkt. Comm.*	Data	Customer Heterogeneity & Time-Varying Effects of Marketing	Latent Mkt. Comm. Stock	Perceived Importance of Different Values	Marketing Resources Allocation Strategy	Modeling Approach	Findings
Bolton et al. (2003)	Yes	Yes	No	Mail survey	No	No	No	No	Two-Stage Least Squares	Find how economic and social (i.e., relational) service resources influence customers' evaluations of business relationships
Palmatier et al. (2006)	Yes	Yes	No	Mail survey	No	No	No	Yes	Hierarchical Linear Model	Empirically test the model that links three types of relationship marketing investments to financial outcomes
Luo and Kumar (2013)	No	Yes	No	Transaction & Mkt. data (social marketing)	Yes	Yes	No	Yes	Hierarchical Bayesian Bivariate Tobit HMM	Retrieve customer's relationship state to measure the return on mkt. investments
Zhang et al. (2014)	Yes	No	No	Transaction & Mkt. data (price negotiation)	Yes	No	No	Yes	Hierarchical Bayesian Multivariate non-Homogeneous HMM	Develop optimal targeted pricing strategies to maximize firm profits
This Study	Yes	Yes	Yes	Transaction & Mkt. data (economic & relational mkt. comm.)	Yes	Yes	Yes	Yes	State Space Model	Estimate the dynamic effects of economic & relational mkt. efforts and link them to customer revenue

*Mkt.: Marketing, Comm.: Communication

Table 2. Keywords to Categorize
Economic and Relational Marketing Communication

	Economic Marketing Communication		**Relational Marketing Communication**	
Defining Characteristics	Offer immediate economic resources. Efforts focused on making the relationship more financially attractive and increase economic satisfaction.		Offer immediate relational/social resources. Efforts focused on making the relationship more personal and socially attractive and increase noneconomic satisfaction.	
Examples of Keywords[7]	money	quantify	satisfaction	address
	rates	save	treatment	check-up
	quote	promotion	advice	follow-up
	financial benefits	comparison	information	services
	pricing	economic	respect	support
	discounts	products	concern	issues
	competitor price	estimates	needs	complaints
	worth	cost reduction	assistance	figure out
	invoice	billing	training	best interests
	negotiate	offer	help	personal situation

Sources: Berry (1995); Bolton, Smith, and Wagner (2003); Dwyer, Schurr, and Oh (1987); Gassenheimer, Houston, and Davis (1998); Palmatier, Gopalakrishna, and Houston (2006)

Table 3. Descriptive Statistics (N=675)

Variable	Mean	S.D.	Min.	Max.
Total number of purchase events (in month)	40.65	11.59	2	48
Purchase revenue per month ($)	1227.94	1341.05	9.38	16209.67
Total number of direct marketing contacts (in month)	8.47	5.83	3	45
Total direct marketing efforts per month ($)	36.21	32.12	0.75	210.21
Economic marketing efforts per month ($)	17.47	17.86	0.24	178.73
Relational marketing efforts per month ($)	18.73	21.53	0.24	181.94
Employee size	14.32	30.91	2	400

[7] Synonyms of these key words were added to the current list using a thesaurus.

Table 4. Pairwise Correlation Coefficients (N=32,400)

Variable	1	2	3	4	5	6
1. Purchase revenue	1					
2. Economic marketing communication	0.077**	1				
3. Relational marketing communication	0.095**	0.242**	1			
4. Cumulative average purchase revenue in the last month	0.505**	0.019*	0.025**	1		
5. Cumulative average cross-buy level in the last month	0.371**	0.018**	0.029**	0.291**	1	
6. Cumulative average price per unit in the last month	-0.034**	-0.007	-0.006	-0.017**	-0.022**	1

Note: **Correlation is significant at the 0.01 level
*Correlation is significant at the 0.05 level

Table 5. Model Estimation Results

	Posterior Mean	Posterior Standard Error
Estimates in the State Equations		
Latent Stock of Direct Marketing Communication (I_{it}) - *Estimates in Equation (2)*		
Time Invariant Intercept ($\overline{\delta_0}$)	4.36	0.14*
Time Invariant Intercept Heterogeneity (V_{δ_0})	0.77	0.09*
Carryover Mean ($\overline{\delta_1}$)	0.61	0.07*
Carryover Heterogeneity (V_{δ_1})	0.54	0.03*
Effect of Past EM (δ_2)	0.39	0.001*
Effect of Past RM (δ_3)	0.60	0.001*
Effect of Past EM and RM Interaction (δ_4)	0.21	0.002*
Perceived Importance of Economic Value (α_{it}) - *Estimates in Equation (3)*		
Time Invariant Perceived Importance of EV Mean ($\overline{\theta_0}$)	0.61	0.05*
Time Invariant Perceived Importance of EV Heterogeneity (V_{θ_0})	0.56	0.06*
Carryover Mean ($\overline{\theta_1}$)	0.55	0.05*
Carryover Heterogeneity (V_{θ_1})	0.38	0.07*
Effect of past EM (θ_2)	0.26	0.003*
Perceived Importance of Relational Value (β_{it}) - *Estimates in Equation (4)*		
Time Invariant Perceived Importance of RV Mean ($\overline{\gamma_0}$)	0.44	0.06*
Time Invariant Perceived Importance of RV Heterogeneity (V_{γ_0})	0.70	0.07*
Carryover Mean ($\overline{\gamma_1}$)	0.64	0.07*
Carryover Heterogeneity (V_{γ_1})	0.33	0.06*
Effect of past RM (γ_2)	0.28	0.002*
Initial States		
Initial State of Intercept Mean (mi_1)	1.70	0.11*
Initial State of Intercept Heterogeneity (pi_1)	0.16	0.05*
Initial State of Perceived Importance of EV Mean (ma_1)	0.28	0.07*
Initial State of Perceived Importance of EV Heterogeneity (pa_1)	0.30	0.04*
Initial State of Perceived Importance of RV Mean (mb_1)	-0.21	0.06*
Initial State of Perceived Importance of RV Heterogeneity (pb_1)	0.56	0.06*
Estimates in the Observation Equation		
Cumulative average purchase revenue in the last month (λ_1)	0.75	0.01*
Last purchase in over 6 months ago (λ_2)	-10.32	1.32*
Cumulative average cross-buy level in the last month (λ_3)	17.11	3.09*
Cumulative average price per unit in the last month (λ_4)	-1.30	0.13*
Industry 1 dummy (ζ_1)	-13.59	2.72*
Industry 2 dummy (ζ_2)	6.29	1.32*
Industry 3 dummy (ζ_3)	4.93	1.28*
Industry 4 dummy (ζ_4)	1.83	1.12
Industry 5 dummy (ζ_5)	1.40	1.36
Industry 6 dummy (ζ_6)	-9.04	1.59*
Employee size (ζ_7)	0.22	0.03*
EM endogeneity correction	-1.59	0.24*
RM endogeneity correction	-2.71	0.45*

Note: *95% coverage interval does not span zero

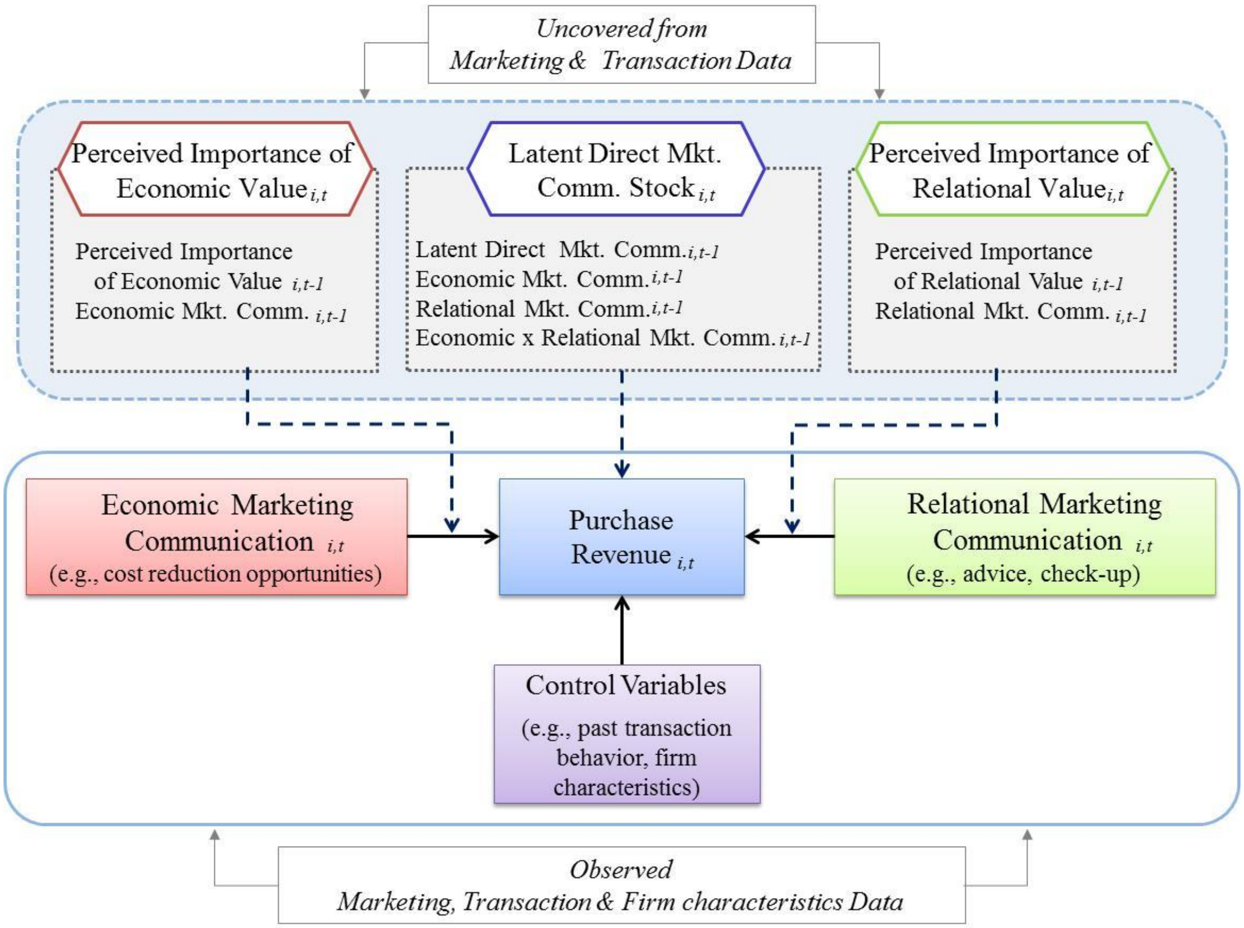
EM: Economic Marketing, RM: Relational Marketing, EV: Economic Value, and RV: Relational Value

Table 6. Model Performance Comparison

Model	Hit Ratio		RAE	
	In-sample	Out-of-sample	In-sample	Out-of-sample
Proposed Model	91.2%	90.0%	–	–
Benchmark Model 1 (base model)	79.4%	78.1%	0.14	0.13
Benchmark Model 2 (only accounting for heterogeneity)	83.5%	80.0%	0.34	0.32
Benchmark Model 3 (only accounting for dynamics)	86.2%	84.7%	0.42	0.39
Benchmark Model 4 (state space model with no contemporaneous marketing)	88.3%	86.5%	0.83	0.80

Note: Relative Absolute Error (RAE) is the mean absolute deviation of the predicted purchase revenue from the proposed model relative to the mean absolute deviation of the benchmark model.

Figure 1. Conceptual Framework



*Mkt.: Marketing, Comm.: Communication

Figure 2. Overview of Empirical Analysis

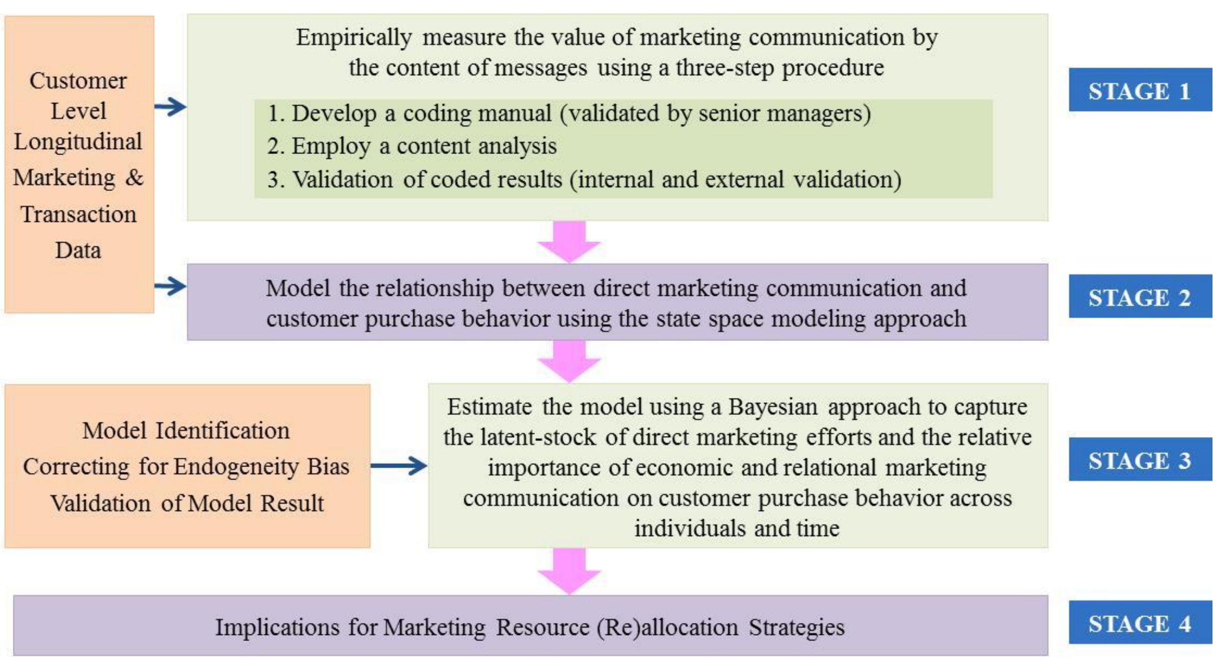
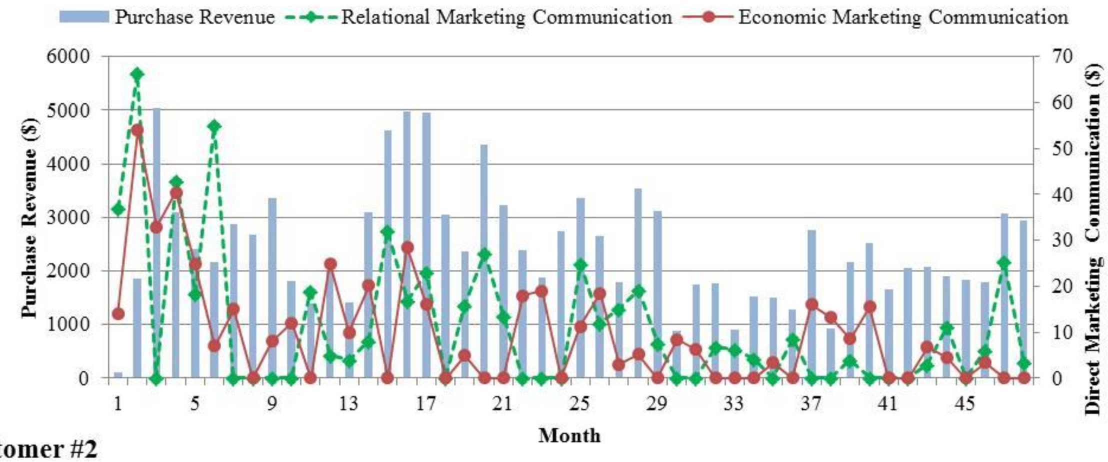


Figure 3. Model Free Evidence

A. Customer #1



B. Customer #2

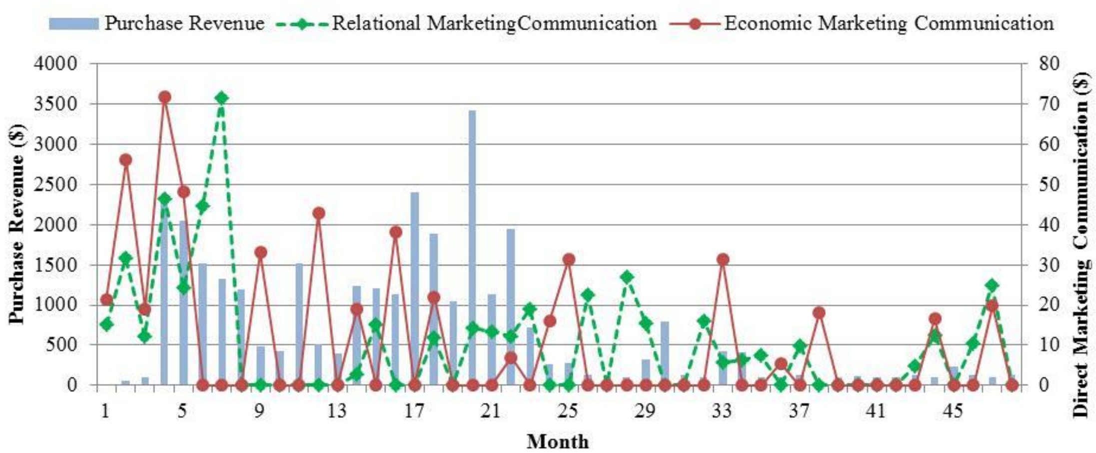
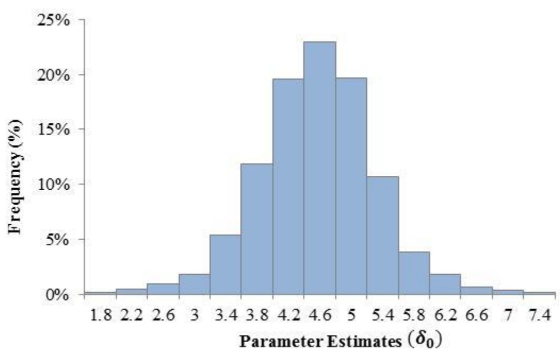
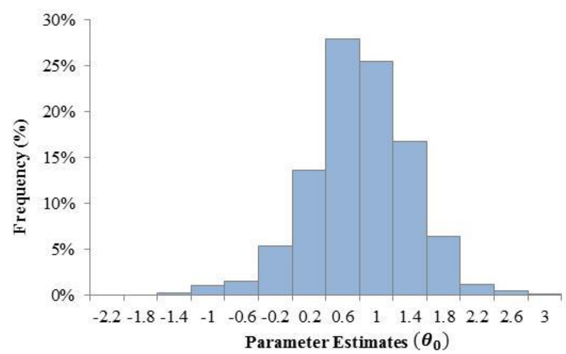


Figure 4. The Histogram of Parameters in State Equations

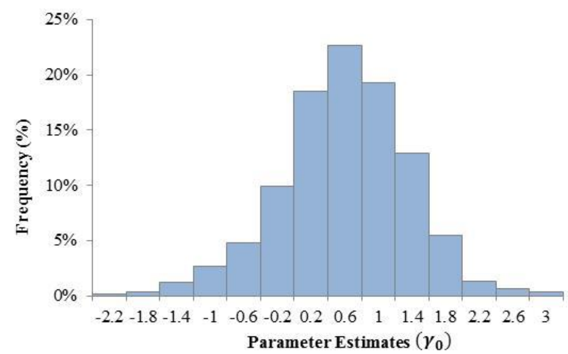
A. Time Invariant Latent Stock of Direct Marketing Communication



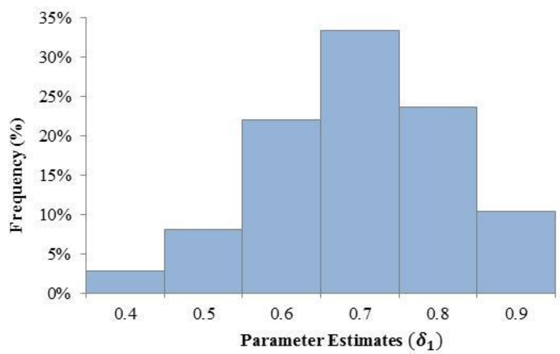
B. Time Invariant Perceived Importance of Economic Value



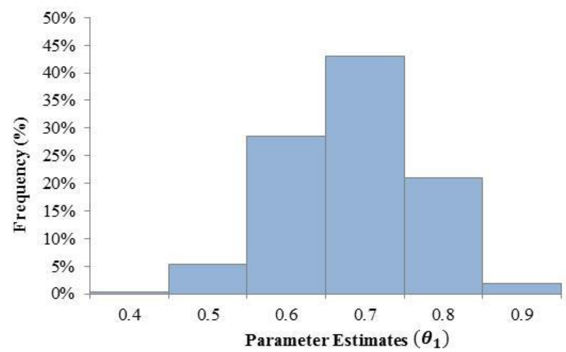
C. Time Invariant Perceived Importance of Relational Value



D. Carryover Effect of Latent Stock of Direct Marketing Communication



E. Carryover Effect of Perceived Importance of Economic Value



F. Carryover Effect of Perceived Importance of Relational Value

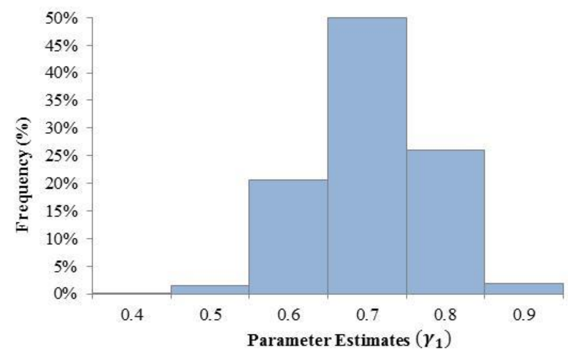


Figure 5. Customer Level Differences by Perceived Importance

		Low Perceived Importance of Relational Value		High Perceived Importance of Relational Value	
High Perceived Importance of Economic Value		Employment size[1]	11.52	Employment size	19.83
		Purchase revenue per month ($)[1]	1244.82	Purchase revenue per month ($)	1600.91
		Industry 1	+15%	Industry 1	-8%
		Industry 2	-9%	Industry 2	+10%
		Industry 3	+11%	Industry 3	+4%
		Industry 4	-6%	Industry 4	+9%
		Industry 5	-8%	Industry 5	-6%
		Industry 6	-14%	Industry 6	-1%
Low Perceived Importance of Economic Value		Employment size	6.88	Employment size	32.52
		Purchase revenue per month ($)	832.48	Purchase revenue per month ($)	1096.95
		Industry 1	+6%	Industry 1	-13%
		Industry 2	+2%	Industry 2	-4%
		Industry 3	-5%	Industry 3	-10%
		Industry 4	-8%	Industry 4	+6%
		Industry 5	+4%	Industry 5	+10%
		Industry 6	+2%	Industry 6	+13%

Note: The industry with the highest proportion of customers is highlighted in green and the lowest proportion of customers is highlighted in red.

APPENDIX A – ESTIMATION ALGORITHM

For notational simplicity, we can rewrite the observation as well as the state equations of equations (1)-(4) as follows:

Observation equation: $Y_{it}{}^{*} = S_{it}X_{it} + aZ_{it} + \varepsilon_{it}$ where $\varepsilon_{it} \sim N(0, \sigma^2)$ (A1)

State equations: $S_{it} = d_i S_{it-1} + bQ_{it} + h_i + v_{it}$ where $v_{it} \sim N(0, \sigma^2{}_v)$ (A2)

Here, X_{it}, Z_{it}, and Q_{it} are the matrix of observed data. X_{it} includes the two focal marketing variables and a vector of 1 for the intercept. Θ includes the parameters (i.e., a, d_i, b, h_i, σ^2, $\sigma^2{}_v$, ms_1, ps_1) that need to be estimated.

1. We first augment the censored values for Y_{it} and draw samples from truncated normal distributions by adopting the approach in a Tobit censored regression model (Chib 1992). We sample c_{it} which will replace the left censored observations ($Y_{it} = 0$) from the truncated normal distribution. After augmenting the data, we have the new data $Y_{it}{}^{*} = (Y_{it}, c_{it})$, where censored observations are replaced with c_{it}. Using the augmented dataset, we can now consider the parameter estimation procedure for the Type I Tobit model similar to the estimation method for the linear regression model.

2. We rewrite the observation equation (A1) to account for marketing endogeneity such that

$$Y_t{}^{*} = S_{it}X_{it} + aZ_{it} + \tau\hat{\mu}_{it} + \tilde{\varepsilon}_{it} \text{ where } \tilde{\varepsilon}_{it} \sim N(0, \widetilde{\sigma^2}) \quad \text{(A3)}$$

We use control function approach for the two marketing variables, where $X_{it} = \omega P_{it} + \mu_{it}$ with P_{it} to be the instrumental variables and that estimated residuals $\hat{\mu}_{it}$ are included in the observation equation.

3. There are five sets of priors that are used in the Gibbs sampler, the priors on (1) the initial state ($I_{i1}, \alpha_{i1}, \beta_{i1}$) which is relevant to S_{i1} in (A2), (2) the customer heterogeneity in

the state equations $(\delta_{0i}, \theta_{0i}, \gamma_{0i})$ which is relevant to h_i in (A2), (3) the carry-over rates in the state equations $(\delta_{1i}, \theta_{1i}, \gamma_{1i})$ which is relevant to d_i in (A2), (4) random errors in the state equations $(\omega_{it}, \eta_{it}, \nu_{it})$ which is relevant to v_{it} in (A2), and (5) random errors in the observation equations (ε_{it}) which is relevant to ε_{it} in (A1).

a) Priors on initial states, $S_{i1} \sim N(ms_1, ps_1)$, where $ps_1 \sim IG(v_{0_{ps}}, V_{0_{ps}})$ and $ms_1 | ps_1 \sim N(\overline{ms_1}, \frac{ps_1}{\tau_{ps_1}})$

b) Priors on customer heterogeneity in the state equations, $h_i \sim N(\bar{h}, V_h)$, where $V_h \sim IG(v_{0_h}, V_{0_h})$ and $\bar{h} | V_h \sim N(\bar{\bar{h}}, \frac{V_h}{\tau_h})$

c) Priors on the carry-over rates in the state equations, $\tilde{d}_i \sim N(\bar{d}, V_d)$[8], where $V_d \sim IG(v_{0_d}, V_{0_d})$ and $\bar{d} | V_d \sim N(\bar{\bar{d}}, \frac{V_d}{\tau_d})$

d) Priors on the random errors in the state equations, $v_{it} \sim N(0, {\sigma^2}_v)$, where ${\sigma^2}_v \sim IG(v_{0_v}, V_{0_v})$

e) Priors on the random errors in the observation equation, $\tilde{\varepsilon}_{it} \sim N(0, \widetilde{\sigma^2})$, where $\widetilde{\sigma^2} \sim IG(v_{0_e}, V_{0_e})$

4. Given the prior, we generate draw the states (S_{it}) recursively using Kalman filtering (Durbin and Koopman 2012). The Kalman filtering process generates $S_{it} | {Y_{it}}^*, \Theta, Q_{it}$ where $\Theta = \{a, d_i, b, h_i, \widetilde{\sigma^2}, {\sigma^2}_v, ms_1, ps_1\}$.

[8] Since the autoregressive parameters are parameterized , $\tilde{d}_i = \exp(\tilde{d}_i)/(1 + \exp(\tilde{d}_i))$

APPENDIX B – SIMULATION STUDY

To evaluate the ability of the model to recover the model parameters without identification issue, we perform a simulation study. We first simulate the direct marketing communications and other control variables mimic the data used in the study with 500 clients, 48 time periods. Using the generated heterogeneous and time-varying parameters given the true values, we simulate the latent purchase revenue each client spends in each time period. As in the data, the purchase revenues are censored in the simulated data. By generating 50,000 iterations and discarding first 25,000 iterations as the burn-in period, we use a total of 25,000 iterations for the model inference. We present the results from the simulation exercise in Table B. The results reveal that we are able to recover the true parameters for all cases within a 95% confidence interval confirming that the estimation algorithm can recover the true parameters to a satisfactory degree.

Table B. Simulation Study Results

	Estimated Values		
	Posterior Mean	**Posterior Standard Error**	**True Values**
Estimates in the State Equations			
Latent Stock of Direct Marketing Communication (I_{it}) - *Estimates in Equation (2)*			
Time Invariant Intercept ($\overline{\delta_0}$)	9.92	0.08*	10.00
Time Invariant Intercept Heterogeneity (V_{δ_0})	2.84	0.10*	3.00
Carryover Mean ($\overline{\delta_1}$)	0.91	0.09*	0.90
Carryover Heterogeneity (V_{δ_1})	0.39	0.01*	0.40
Effect of Past EM (δ_2)	0.68	0.01*	0.70
Effect of Past RM (δ_3)	0.28	0.02*	0.30
Effect of Past EM and RM Interaction (δ_4)	0.49	0.006*	0.50
Perceived Importance of Economic Value (α_{it}) - *Estimates in Equation (3)*			
Time Invariant Perceived Importance of EV Mean ($\overline{\theta_0}$)	0.74	0.03*	0.70
Time Invariant Perceived Importance of EV Heterogeneity (V_{θ_0})	0.55	0.04*	0.50
Carryover Mean ($\overline{\theta_1}$)	0.18	0.02*	0.20
Carryover Heterogeneity (V_{θ_1})	0.45	0.08*	0.50

Effect of past EM (θ_2)	0.09	0.01*	0.10
Perceived Importance of Relational Value (β_{it}) - *Estimates in Equation (4)*			
Time Invariant Perceived Importance of RV Mean ($\overline{\gamma_0}$)	0.32	0.04*	0.30
Time Invariant Perceived Importance of RV Heterogeneity (V_{γ_0})	0.81	0.06*	0.70
Carryover Mean ($\overline{\gamma_1}$)	0.72	0.04*	0.70
Carryover Heterogeneity (V_{γ_1})	0.64	0.03*	0.70
Effect of past RM (γ_2)	0.29	0.01*	0.30
Initial States			
Initial State of Intercept Mean (mi_1)	1.97	0.09*	2.00
Initial State of Intercept Heterogeneity (pi_1)	0.21	0.11*	0.30
Initial State of Perceived Importance of EV Mean (ma_1)	0.37	0.16*	0.40
Initial State of Perceived Importance of EV Heterogeneity (pa_1)	0.52	0.27*	0.50
Initial State of Perceived Importance of RV Mean (mb_1)	0.46	0.19*	0.50
Initial State of Perceived Importance of RV Heterogeneity (pb_1)	0.63	0.32*	0.80
Estimates in the Observation Equation			
Cumulative average purchase revenue in the last month (λ_1)	0.89	0.01*	0.90
Last purchase in over 6 months ago (λ_2)	-8.12	0.33*	-8.00
Cumulative average cross-buy level in the last month (λ_3)	20.06	0.25*	20.00
Cumulative average price per unit in the last month (λ_4)	-5.25	0.15*	-5.00
Industry 1 dummy (ζ_1)	-15.17	0.27*	-15.00
Industry 2 dummy (ζ_2)	-6.83	0.20*	-7.00
Industry 3 dummy (ζ_3)	-3.30	0.23*	-3.00
Industry 4 dummy (ζ_4)	-5.59	0.29*	-5.00
Industry 5 dummy (ζ_5)	4.81	0.30*	5.00
Industry 6 dummy (ζ_6)	10.60	0.31*	11.00
Employee size (ζ_7)	0.48	0.04*	0.50

Note: *95% coverage interval does not span zero

APPENDIX C – ADDRESS MARKETING ENDOGENEITY

Table C1: Estimates of Regressing Economic Marketing Communication on Instruments

	Estimate	S. E.
Intercept	-0.298	0.077***
Total Economic Marketing Communication ($) in the Previous Quarter to customers in the same industry	0.139	0.025***
Total Economic Marketing Communication ($) in the Previous Quarter to customers in the same geographic location	0.079	0.023***
Average Marketing Communication ($) per contact in the Previous Quarter to customers in the same industry	0.811	0.149***
Average Marketing Communication ($) per contact in the Previous Quarter to customers in the same geographic location	0.502	0.204**
Growth in Total Purchase Revenue ($) over the Previous Quarter	0.032	0.001***
Model Statistics		
Number of Observations	32,400	
R-square (Adjusted R-square)	0.6334 (0. 6333)	

Note: ***p<0.001 **p<0.05 *p<0.1

Table C2: Estimates of Regressing Relational Marketing Communication on Instruments

	Estimate	S. E.
Intercept	-0.171	0.022***
Total Relational Marketing Communications ($) in the Previous Quarter to customers in the same industry	0.195	0.044***
Total Relational Marketing Communications ($) in the Previous Quarter to customers in the same geographic location	0.055	0.028**
Average Marketing Communication ($) per contact in the Previous Quarter to customers in the same industry	0.972	0.231***
Average Marketing Communication ($) per contact in the Previous Quarter to customers in the same geographic location	0.340	0.112**
Growth in Total Purchase Revenue ($) over the Previous Quarter	0.043	0.002***
Model Statistics		
Number of Observations	32,400	
R-square (Adjusted R-square)	0.6102 (0. 6101)	

Note: ***p<0.001 **p<0.05 *p<0.1