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Defining, Measuring, and Managing Business Reference Value

It is common for business-to-business firms to use references from client firms when trying to influence prospects to become new customers. In this study, the authors define the concept of business reference value (BRV) as the ability of a client's reference to influence prospects to purchase and the degree to which it does so. They develop a three-step method to compute BRV for a given client using a retrospective reported measure of reference value. Next, they use data from a financial services and a telecommunications firm to identify and empirically test the drivers of BRV. These drivers fall into four categories: (1) length of client relationship, (2) client firm size, (3) reference media format, and (4) reference congruency. Next, the authors empirically show that clients that have the highest BRV are not the same as the clients that have the highest customer lifetime value. They also show that an average client that is high on BRV has significantly different characteristics from the average client that is low on BRV. Finally, they derive implications for managing BRV.

Keywords: client references, business reference value, customer lifetime value, business-to-business marketing

Many firms are trying to capitalize on the power of client reference behavior as part of their general marketing and sales efforts to encourage new customer adoption. For business-to-business (B2B) firms especially, the use of referencing behavior is often the only alternative for leveraging the value of current clients on new customer adoption through social influences. For B2B firms, the use of referencing behavior is important because, unlike for business-to-consumer (B2C) firms, the purchase decision process often does not rely on other social influences such as word of mouth (WOM) or referrals from other businesses. For example, Microsoft has created a Customer Reference Program to influence prospects to adopt their products and services.[1] The firm does so by directing prospects to a website that contains case studies and white papers from a sample of current clients, selected by Microsoft to represent what its sales executives believe are the best examples of successful implementations of Microsoft products and services. These case studies serve as references from current clients that Microsoft uses to influence prospects to adopt.

To date, there has been limited research explaining the social influences present in B2B settings (Libai et al. 2010). Therefore, it is not yet clear how seller firms can quantify the value that these references provide, whether seller firms are able to determine which clients are likely to be the most valuable references for new customer acquisition, or which reference formats are the most effective at influencing prospects to adopt. In this study, we focus on further understanding the role and value of client references, specifically in a B2B selling context. We aim to answer the following four key research questions:

1. Can we measure the value of a business reference from a client?
2. What are the key drivers, both in terms of the referencing client and the format of reference, of the value of the reference?
3. Are clients that generate valuable references the same ones that are the most profitable in terms of their own purchasing behavior to the seller firm?
4. What types of clients tend to generate high-value references?

Our first step before we begin to answer these four questions is to determine how business references play a role in the adoption of prospects in a B2B setting. We do so by leveraging the rich literature in marketing on the buying processes of B2B firms and through qualitative interviews with managers from B2B firms who are directly involved in making purchase decisions with their respective firms. We use the literature review and the qualitative interviews to develop a conceptual model of the drivers of reference selection (which client to select as a reference) and reference value (how much business the reference will bring in

[1]For an example of Microsoft's Customer Reference Program, see http://www.microsoft.com/hk/sia/default.mspx.

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monetary value). In addition, we hypothesize how each of these drivers is likely to affect the process of selection and value of the reference.

Then, to empirically answer the four key questions, we use data from a B2B financial services firm and a telecommunications firm that focus on selling products and services to mainly small to medium-sized businesses, for which the purchase situations tend to be simple. Examples of these products and services include business checking/savings (financial services) and commercial/business landline telephone service (telecommunications). (For a more detailed list of product categories, see the Web Appendix at www.marketingpower.com/jm_webappendix.) We focus specifically on these two firms' customer acquisition efforts in which none of the potential client firms had purchased from the focal selling firms or, likely, from any of the firms' competitors. This means that the potential client firms may have some general product category experience, which includes any personal experience using financial services and telecommunications products and services, but none of the potential client firms would have any specific product or focal firm experience in this context to rely on in the purchase situation. Given the churn faced by many B2B firms that rely on generating new customers, this is a common situation and makes using references a key part of the potential client firm's decision to adopt. In addition, most of these small to medium-sized potential client firms likely have few key decision makers, making it easier to obtain accurate information regarding the influence of references on adoption. In addition, the selling firms use some other selling and marketing efforts, including product brochures, some general branding efforts on the firms' websites, and a sales force that calls on potential client firms, providing some potential variance in the effect of references on adoption.

Thus, this study makes three key contributions to the marketing literature. First, we define the concept of business reference value (BRV), which is the ability of a client's reference to provide monetary value to the seller firm by influencing a prospect to adopt and the degree to which it does so. We measure the BRV of each referencing client and the customer lifetime value (CLV) of each referencing client and newly acquired client from the prospect pool. To do this, we develop a new three-step method for computing BRV using a retrospective reported measure of reference value, which includes information about how much each reference influenced each prospect to purchase and the value of the new customer.

Second, we empirically determine the key drivers of BRV using data from the two selling firms in this study. We find that the characteristics of the referencing client, the characteristics of the prospect, and the characteristics of the reference are all significant predictors of reference selection and/or BRV. These key drivers include length of client relationship, client firm size, reference congruency, and reference media format. These results help us better understand which references are likely to be most effective in converting prospects to clients.

Third, we deconstruct the measure of BRV to determine the role of each of the three measures (Ref_n, DOI_{in}, and CLV_n) in driving BRV. We find that, in general, most firms that were acquired during the sales process were highly influenced by references in making their decisions (high Ref_n). We also find that many of these firms only relied on a few references in making their decisions (low number of firms with positive DOI_{in}). Finally, we find a significant variance in the profitability of the newly acquired customers (high variance in CLV_n), suggesting that references influence low- and high-value customers to adopt.

Theoretical Foundations

Literature Review

Business-to-business firms' decision to purchase, when compared with B2C firms, is often more complex and drawn out. This is because purchases made by organizations tend to rely on many different employees within the organization (i.e., a buying center) and on budget, cost, and profit considerations (Webster and Wind 1972). As a result, seller firms' sales endeavors are often multidimensional and can include both personal and impersonal sources along with commercial and noncommercial sources (Moriarty and Spekman 1984). Seller firms can influence the organizational buying decisions of prospects through different sources, timing, and quality of information. Moriarty and Spekman (1984) offer empirical evidence showing that the seller firm uses personal noncommercial information sources such as social influences (e.g., references) throughout the decision process. These influences can become most important during the later stages of the buying process and often can be what distinguishes one company from another becoming the "order winner." Although not empirically tested in the literature, this suggests that seller firms that employ references during the sales process can significantly influence an organizational buyer's decision to make a purchase.

During the organizational buying decision process, there are four key drivers that affect the prospect's propensity to adopt: (1) firm-initiated efforts (e.g., direct/mass communication), (2) competitor-initiated efforts (e.g., competitor direct/mass communication), (3) client-initiated efforts (e.g., references), and (4) prospect characteristics (e.g., demographics) (Prins and Verhoef 2007; Reinartz, Thomas, and Kumar 2005; Villanueva, Yoo, and Hanssens 2008). Because the objective of this study is to investigate how client-initiated efforts influence B2B prospects to make a purchase, we focus specifically on the research that explains the relationship between client-initiated efforts and customer adoption for organizational buyers, which is relatively scarce (Libai et al. 2010).

Wangenheim and Bayón (2007) analyze the linkages between customer satisfaction, WOM, and new customer acquisition for both B2C and B2B customers in the German energy-provider market. They find that managers of B2B firms rely on WOM for their purchase decisions, and WOM affects new customer acquisition. However, it is unclear whether the source of the WOM was a manager or a consumer, making it difficult for a seller firm to harness the power of WOM for the purposes of enhancing customer acquisition.

Hada, Grewal, and Lilien (2011) show through a mixed-design experiment how supplier firms make trade-offs when selecting references for prospects. They find that increasing the similarities between the client and the prospect provides significant benefit to the manager's evaluation of the referral. Although this study relates directly to a B2B context, the outcome these authors are interested in is manager evaluation of the reference, whereas in our study, we are interested in determining the value of the reference to the seller firm.

Stephen and Toubia (2010) analyze a group of online social commerce networks, in which the networks involve individual sellers linking their online marketplace with other sellers, creating a virtual mall. The authors find that allowing sellers to connect with each other provides significant economic value, especially to those whose accessibility is most enhanced by the network. Although this study analyzes social connections between sellers, it is focused on firms that are trying to become more effective at selling products and services to end consumers.

Godes (2012) uses an analytical model to uncover the benefits to early and late adopters as a result of the seller firm announcing a referencing program. He finds that one of the key benefits of announcing a referencing program is that early adopters are willing to pay more because of the increase in information transmission and information transparency—a benefit for late adopters as well. Thus, the referencing program can be viewed as a substitute for an exclusive use contract. While Godes shows that referencing programs do add value, he does not suggest how seller firms should select and use client firm references to maximize profitability.

Thus, while there have been several studies that generally analyze some aspects of social influence on organizational purchase decisions, we know of no study that has specifically investigated how selling firms can understand how to use client references to effectively drive customer acquisition and how to value those client references, a key contribution of this study.

Qualitative Interviews

To better understand the role of references in the organizational buying process, we conducted qualitative interviews with 26 executives from small to medium-sized businesses who play a key role in the purchase decision making for their respective firms. These executives participated in a sales and marketing workshop organized by an executive education forum in the southeast United States over two days. On Day 1, we interviewed 14 executives, and on Day 2, we interviewed 12 more executives. Each interview lasted for approximately 30 minutes and was conducted individually. The same person conducted all the interviews. The objective of these qualitative interviews was to determine whether the executives believe that references influence their decision making. In addition, when they make purchase decisions, we asked to what extent references influence the decision to purchase when compared with the other marketing and sales efforts. Finally, we asked at what point during the purchase process the references had an impact on the decision to purchase. We selected these executives for the qualitative interviews because many represented small to medium-sized businesses similar to the potential client firms being targeted by the focal firms in our empirical application.

The results from our analysis of the qualitative interviews suggest that references play a key role in the purchase decision process for many of these organizations. Indeed, our qualitative interviews show that many managers from these businesses rely on references throughout the purchase decision process, especially just before the buying decision is made. As one manager from the buying firm noted,

> The list of references provided by the seller helps us to shortlist the seller firms. However, to finally decide on whom to buy from, we check at least a couple of references provided by the seller shortly before our purchase decision. We also discuss internally as to how much influence the references had on our buying decisions.

The results of the interviews with the executives also suggested that those references that provided the most value in influencing the purchase decision were those from reputable firms; had the highest similarities to the buyer firm (whether it was in terms of products or services purchased, industry of the referencing client, or job function of the referencing client); and were provided through richer media formats.

We also interviewed 12 B2B managers from the supplier firms about the use of references by their prospective clients. According to the chief executive officer of Pinnacle Promotions (who represents the typical sentiments of the remaining respondents),

> Our clients use the list of references we provide to reduce the choice of suppliers. Once we get into the decision-making stage, our participants ask us [for] specific references. We provide access to multiple forms of references, different types of clients, and different job descriptions of the person providing the reference. Our prospects are free to choose whichever reference they like to pursue.

We used the results of these qualitative interviews to help guide the development and empirical testing of our conceptual model.

Conceptual Framework and Hypothesis Development

Our goal is to understand the key drivers of reference selection by the seller firm and the drivers of BRV for each client reference. Specifically, we argue that firms strategically select as references current client firms that are likely to maximize the profitability from potential client firm purchase behavior. In addition, we argue that potential client firms make decisions to adopt to maximize the benefit they receive from the relationship with the seller firm. Both situations are driven by similar theoretical constructs. Research suggests that a potential client firm's decision to adopt (i.e., build a strategic alliance) is driven by examining the current alliances that the seller firm has built (Gulati and Gargiulo 1999). Moreover, the strength of these current alliances depends on the "trusted informants" (or references) provided by the seller firm and the degree to which those informants are embedded in the seller firm. In addition, the ability of the information transferred from the trusted informant to the potential client firm to be understood and relatable depends on the richness of the communication and the degree to which the information provided is similar to the business situation the potential client firm faces. Thus, seller firms should select trusted informants to pass along the most valuable information to potential client firms.

From this discussion, we believe that there are four key drivers of reference selection and reference value: (1) the degree to which the client firm can be viewed as a trusted informant through client firm size, (2) the degree to which the client firm has built a strategic alliance with the seller firm through length of client relationship, (3) the ability of the communication to convey information to the potential client firm through reference media format, and (4) the degree to which the information provided is relatable to the potential client firm through reference congruency. Figure 1 shows a graphic representation of these drivers.

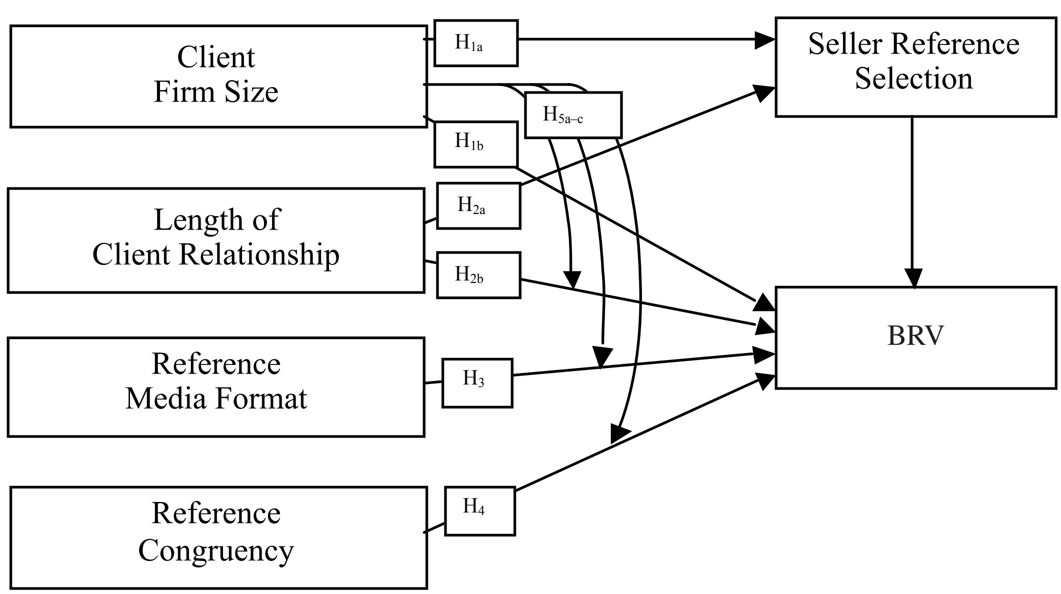
During the sales process, it is common for many B2B firms to use references from clients as a tool to influence a prospect to adopt a product/service. Thus, the process of using references to influence the purchase process breaks down into two distinct steps. First, the seller firm selects the clients in its current database to act as references to be used during the sales efforts. Second, the sales force uses the references to influence the prospects to adopt. We anticipate that these prospects will evaluate the value of the reference on the basis of several key characteristics.

In the next section, we develop the hypotheses related to the drivers of reference selection and BRV. We anticipate that differences in the referencing client characteristics will affect the reference selection strategy of the seller firm. We also anticipate that the reference selection strategy, the referencing client characteristics (in terms of firm size and relationship length), the reference media format, and reference congruency with the prospect will drive the BRV.

Client Firm Size

To use client references to influence prospect adoption, the first step a seller firm must take is to select which firms from its current client database are the best candidates to be references. We anticipate that seller firms select these clients strategically to maximize the impact of the influence of the reference. The seller firm aims to reduce the information cost of search and information asymmetry, with the goal of making the decision to purchase easier for the prospect (Spence 1973). Reducing information asymmetry by providing information that is not otherwise available (i.e., prospects cannot experience the benefits of the product or service until adoption) at a relatively low cost (e.g., through a reference) can be an effective signaling strategy (Connelly et al. 2011). In addition, this information is likely more valuable when the firm is trusted or has a good reputation in the marketplace (Morgan and Hunt 1994). Moreover, large firms tend to receive more public scrutiny than small firms (Fombrun and Shanley 1990). However, even if this information does not always put the firm in a positive view, the mere availability of information about and familiarity with large firms tends to inflate people's opinion of the larger firms' activities (Tversky and Kahneman 1974). As a result, we expect that current client firms whose attributes are visible in the marketplace and are perceived as valuable to the marketplace (e.g., significant size) are more likely to provide an effective reference to prospects through their reputation. Here, we define "client firm size" as the

FIGURE 1
Conceptual Model of the Drivers of BRV



size of the firm in the marketplace, whether it is based on labor force or scale of operations. As a result, we expect that it is in the best interest of the selling firm to strategically select larger client firms to be references. Thus:

H_{1a}: Seller firms are more likely to select larger client firms to be references than smaller client firms.

When consumers rely on external information to help in purchase decisions, they often rely on the credibility of the source as well as the information that is being passed along (Gershoff, Broniarczyk, and West 2001). The source of the reference offers a signal to the prospect about the type of firms that currently purchase from the selling firm (Herr, Kardes, and Kim 1991). Research has shown that the credibility of the source of the WOM in both B2C and B2B cases matters (Wangenheim and Bayón 2007). In addition, in many instances, especially those such as celebrity endorsements (McCracken 1989), the perceived value of the product or service is directly tied to the source. Research has also shown through interviews with managers that source often plays a significant role in the effectiveness of business references (Godes 2008). Moreover, recent research has suggested that the value of the client firm's reputation is often passed along to the seller firm through the reference (Helm and Salminen 2010), where higher reputations tend to be linked to larger firms (Tversky and Kahneman 1974). Thus, we anticipate that the client featured in the reference provides a valuable signal to the prospect merely through its identity in the marketplace, such that larger current clients offer a positive signal to prospects about the quality of the products or services and the quality of the selling firm. Thus:

H_{1b}: Among the client firms selected as references, larger firms are more likely to have higher BRV than smaller firms.

Length of Client Relationship

We expect seller firms to strategically select client references according to the level of embeddedness the client has with the seller firm, where the embeddedness is often stronger when the relationship between the seller and client firm is longer. Here we define length of client relationship as the total expected time of the relationship between the seller and client firm, which includes not only the length of the past relationship but also the expected length of the future relationship. The structure and quality of ties between the referencing client and the seller firm, where a more integrated structure and a higher quality relationship lead to higher expectations of relationship length. Research has shown that longer relationships between organizations increase the likelihood of new product selection (Kaufman, Jayachandran, and Rose 2006). To relate this research to reference selection, it suggests that firms with longer relationships are more likely to be selected as client references. However, research on buyer–seller relationships indicates that overembeddedness (too much relationship length and depth) actually creates a dark side to relationships (Wuyts and Geyskens 2005), suggesting that seller firms are most likely to select clients with a moderate level of relationship length as references. Thus:

H_{2a}: Seller firms are more likely to select client firms that have a longer relationship with the seller firm to a threshold (an inverted U shape) to be references than client firms with a shorter relationship with the seller firm.

We also anticipate that the client's behavior with the seller firm in particular, and not just its firm size, can signal to the prospect about the quality of the seller firm. For example, Heide and John (1990) find that prospects can view a closer relationship between a seller firm and current client as a way to reduce the ambiguity of purchase. However, research in the management literature also suggests that overembeddedness beyond a certain threshold can be problematic because it may indicate to the prospect that the referencing firm is unfamiliar with potential alternatives (Uzzi 1997). As a result, we anticipate that the longer the relationship between the referencing client and the seller firm, the more positive (to a threshold) the signal will be to the prospect. Thus:

H_{2b}: Among the client firm firms selected as references, those with a longer relationship with the seller firm to a threshold (an inverted U shape) are more likely to have a higher BRV than client firms with a shorter relationship with the seller firm.

Reference Media Format

Research has shown that the way the content is delivered and the quality of the information of any marketing communications can play a significant role in for industrial purchasing (Moriarty and Spekman 1984). Thus, the medium and specific format of the reference should also play a key role in determining the value of the reference. We define "reference media format" as the type of reference provided such that different media formats change (1) the amount of information that can be conveyed and (2) the amount of uncertainty of the message content that can be alleviated (Daft and Lengel 1986). For example, research has shown that richer modes of communication are more likely to influence customers to purchase (Venkatesan and Kumar 2004) because they are perceived to have more valuable information content, convey a greater effort by the firm to communicate with the consumer, and potentially provide a more customizable opinion from the client. We anticipate that a reference that provides information in a richer media format is likely to be more effective in influencing a prospect to purchase. Thus:

H_3: The media format of the reference affects the BRV of client firms such that client firms that provide references in a richer media format are more likely to have a higher BRV than clients that provide references in a less rich media format.

Reference Congruency

Another key factor to consider is whether the referencing client is congruent with the prospect. Here we define "reference congruency" as the degree to which there are similarities between the referencing client and the potential client. For example, we observed from the qualitative interviews that prospects may be interested in references from firms from the same industry, firms that purchased similar products or services, or even references from people who hold the same role within their firm (e.g., marketing, operations). Recent research has shown that sellers can benefit from selecting specific referrals for prospects that have a high level of congruency (Hada, Grewal, and Lilien 2011). This homophily between the client providing the reference and the prospect is likely to generate trust and reciprocity (Goldenberg et al. 2009) and strengthen the bond (i.e., tie strength) between the two parties (Brown and Reingen 1987). As a result, we anticipate that references from clients with greater congruency with the prospect are more influential in getting the prospect to adopt. Thus:

> H_4: Client firms that provide references that have a higher degree of congruency with the prospect firm are more likely to have a higher BRV than client firms that provide references that have a lower degree of congruency.

The Incremental Benefit of Firm Size

Research on commitment and trust suggest that when both commitment and trust are present, "they produce outcomes that promote efficiency, productivity, and effectiveness" (Morgan and Hunt 1994, p. 22). We predict that larger firms are a more trusted reference in terms of a stronger signal of quality to the prospect. This suggests that not only should larger firms send a positive signal to the prospect, which serves to reduce the uncertainty of the purchase decision, but they should incrementally strengthen the other drivers of the value of the reference. Thus, after controlling for the main effect of firm size, we hypothesize the following:

> H_{5a}: When client firms are larger, it further strengthens the positive impact of (a) longer lengths of client relationships on BRV, (b) richer reference formats on BRV, and (c) higher congruency on BRV.

We provide a summary of the main hypotheses in Table 1 and the numbers of the hypotheses on the links between the constructs in our conceptual model in Figure 1.

BRV

Measurement of BRV

To empirically test the hypotheses, we first need to develop a measure to compute the value of a business reference. We propose that the value of a business reference is a function of three components: (1) the amount of influence that client references (vis-à-vis other marketing elements) had on a prospect's adoption, (2) the amount of influence that a given client reference (vis-à-vis other client references) had on the prospect's adoption, and (3) the profitability of the prospect after adoption. We represent this mathematically as follows:

$$\text{(1)} \qquad BRV_i = \sum_{n=1}^{N} \frac{Ref_n \times DOI_{in} \times CLV_n}{(1+r)^{t_n}},$$

where

BRV_i = Business reference value of client reference i,
Ref_n = Degree to which references affected the prospect n's purchase decision,
DOI_{in} = Degree of influence of client reference i on converted prospect n,
CLV_n = CLV of converted prospect n,
N = Total number of converted prospect,
r = Discount rate (in months), and
t_n = month that converted prospect n became a customer after the first month of the observation window.

Equation 1 illustrates that we can compute the contribution of BRV from each prospect that chooses to adopt a product or service by multiplying the degree of influence that client references, in general, had on the decision of that prospect to adopt (Ref) by the degree that the given client's reference influenced the prospect to adopt (DOI), and by the profitability of the converted prospect (CLV). When we have this information from each converted prospect, we cal-

TABLE 1
Summary of Hypotheses

Hypothesis	Expected Effect	Rationale
H_{1a}: Client firm size → selection H_{1b}: Client firm size→ BRV	+ +	The larger client firm sends a positive signal, which makes it more likely to be selected as a reference and more likely to have a higher BRV.
H_{2a}: Length of client relationship → selection H_{2b}: Length of client relationship → BRV	∩ ∩	Firms with longer relationships with the seller firm potentially reduce risk and ambiguity of purchasing. Overembedded firms (i.e., too long of a relationship) can be problematic for both selection and level of BRV.
H_3: Reference media format → BRV	+	Richer media formats send a stronger signal and more valuable information, leading to a higher BRV.
H_4: Reference congruency → BRV	+	Homophily between client and prospect strengthen the value of the information leading to a higher BRV.
H_{5a}: Firm size × relationship length → BRV H_{5b}: Firm size × reference media format → BRV H_{5c}: Firm size × reference congruency → BRV	+ + +	When firms are larger, it enhances the strength of the other drivers of BRV. This leads to an incrementally higher value for BRV.

culate the contributions to each client's BRV across all the converted prospects. Now that there is a conceptual understanding of the process to compute BRV, the next step is to create a method for generating values for the three inputs of the BRV equation.

Computation of BRV

Step 1: Determine whether client references influenced adoption. The first step is to determine whether client references in general had any influence on the prospect's decision to adopt. In this case, we expect that the adoption process is driven by two processes: seller-generated and customer-generated marketing. Seller-generated marketing efforts tend to include any direct- or mass-marketing efforts initiated by the seller firm. In this case, client-generated marketing transpires when the seller firm uses information about the client in influencing the prospect (reference). We compute this value using a constant-sum scale approach. At the time of adoption, we asked the converted prospect to do the following:

> Allocate a total of 100 points between the following two influences: (1) the influence of client references in general and (2) the influence of all other marketing processes (e.g. direct, mass, etc.) and sales initiatives (e.g. personal selling).

We assume that the value given to the influence of client references is, in effect, the percentage of the sale that can be attributed to the influence of client references. We then set the score that was given to the influence of references in general to the value of Ref_n.

Step 2: Determine the influence of each client's reference. The second step is to determine the influence that each client reference had on the prospect's decision to adopt. We compute this value using a similar constant sum scale approach as we did for Ref_n. At the time of adoption, assuming a converted prospect had a value of $Ref_n > 0$, we asked the converted prospect to do the following: "Allocate a total of 100 points across each of the client references you felt influenced your decision to purchase (where more points means the reference had a greater influence)."

All 100 points could be allocated to one client reference if all other references had no impact, or the points could be allocated across any combination of client references according to the perceived influence. The value given to each client reference in this step is, in effect, the proportion of influence that a given client's reference had relative to the total influence that client references had on a converted prospect's decision to adopt. We attributed the score given to the influence of each client's reference to the value of DOI_{in}.

Step 3: Compute the CLV of the converted prospect. The third step is to compute the expected future profit, or CLV, of the converted prospect n. We do so by adapting an equation Petersen and Kumar (2009) use to measure a customer's CLV. Petersen and Kumar show at an aggregate level how total customer purchases, total operating costs (i.e., product returns/service costs), and total firm-initiated marketing efforts are equal to profit. We convert this calculation from the aggregate to the customer level:

$$(2) \qquad CLV_n = \sum_{t=1}^{T} \frac{\pi(\text{Purchases}_{nt}) - \pi(\text{Operating Costs}_{nt}) - \text{Marketing}_{nt}}{(1+r)^t},$$

where

CLV_n = CLV of customer n,
$\pi(\text{Purchases}_{nt})$ = Profit from purchases of customer n in time t,
$\pi(\text{Operating Costs}_{nt})$ = Profit lost from operating costs of customer n in time t,
Marketing_{nt} = Marketing costs for customer n in time t,
T = Time horizon of the prediction, and
r = Discount rate (in months).

Equation 2 shows that the CLV for each new customer n is a function of three factors: (1) the profit from purchases, (2) the operating costs, and (3) the marketing costs to retain the customer. In this case, profit from purchases includes the contribution margin from purchases aggregated monthly, profit lost from operating costs includes losses from product returns and/or costs of customer service aggregated monthly, and marketing costs include the costs of any marketing efforts the firm expends to the individual customer n aggregated monthly.

For our empirical example, we conducted a field study during a one-year time period and then observed the purchases, product returns, and marketing efforts for the remainder of the normal CLV prediction window, over a period of three years. In this case, we compute only the actual CLV of converted prospects, not predicting it. In the case in which the entire prediction window is not observed, we could use the method that Reinartz, Thomas, and Kumar (2005) suggest to predict the CLV of newly acquired customers. We then use the resulting value of BRV for each of the client references as a dependent variable with the antecedents of BRV as independent variables to uncover the drivers of BRV.

An Empirical Example

To explain the influence and value of client references, we provide two empirical examples from two B2B firms, one in the telecommunications industry and another in the financial services industry. In the following sections, we describe the data we collected from these two firms, the selection and operationalization of the variables for the constructs, and the method used for estimating the model to empirically determine the drivers of BRV.

Data

The telecommunications firm provides products and services that include landline phone service, voice over Internet Protocol, Internet service, wireless service, maintenance contracts, and infrastructure, among other products. The financial services firm provides products and services that include business checking/savings accounts, payroll deposit services, lines of credit, loans, insurance, and investments among other products. The data collection for both firms spanned a period of six years and included a one-year field study, during which we collected information about the influence of client references. Figure 2 provides a timeline of the data collection process for both firms.

In the first three years (from July 2004 to June 2007), the firms collected historical transaction and firmographic data from the clients that were chosen to be references for prospects. In this case, many of the firms that agreed to be used as references were willing to do so without any incentive. The only compensation given to the seller firm was funds to cover any costs incurred while generating the reference—where the client chose the reference format. There were no rewards (e.g., promotional discounts) for agreeing to be used as a reference. There were 88 clients from the telecommunications firm and 94 clients from the financial services firm used as references during the one-year field study. The data collected from these clients included exchange (e.g., transaction and marketing information) and descriptive (e.g., firmographics) information. In the one-year period immediately following the first three years (from July 2007 to June 2008), both firms conducted a field study in which prospects were shown all the references from the clients that were made available to them during the sales process. Then, all prospects that made their first purchase during this field experiment period filled out a survey, answering two questions about the client references as described in Steps 1 and 2 from the previous section.

There were 31 converted prospects from the telecommunications firm and 37 from the financial services firm that joined during the field experiment period. The firms then tracked the exchange characteristics, which included the transactions (both purchases and operating costs) and marketing information of the referencing clients and the converted prospects, for two more years (from July 2008 to June 2010). We used this information for computing the values of the referencing clients and converted prospects during the three-year data collection period, which included one year of the field test and two years post–field test (i.e. realized CLV).

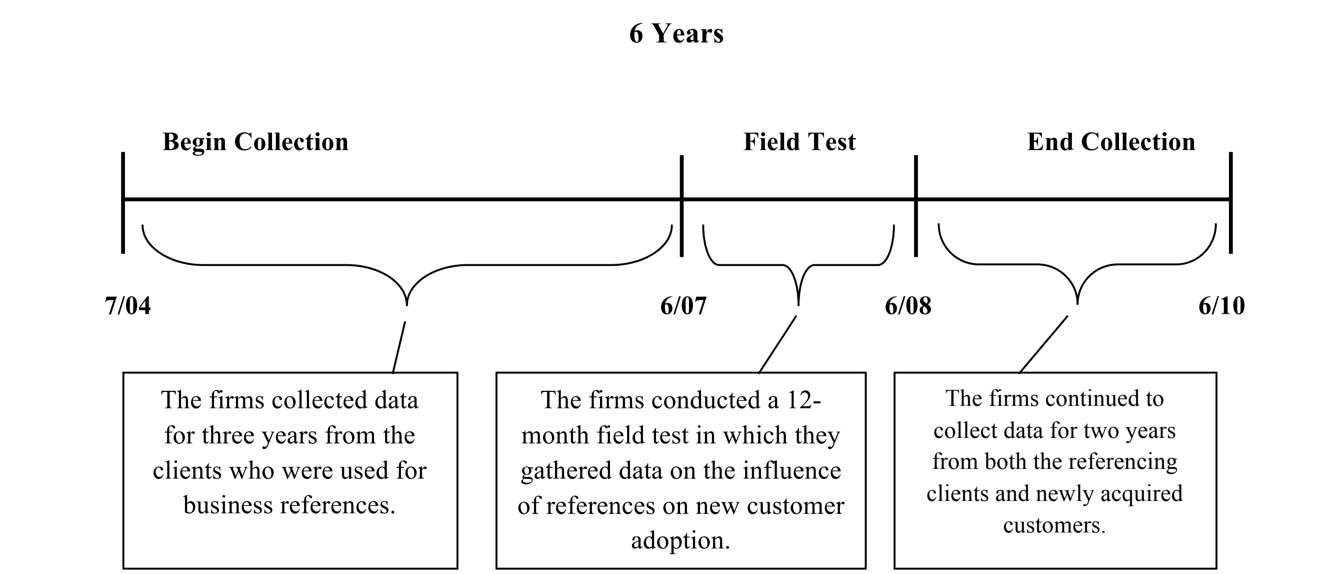
Estimation Method

To empirically determine the drivers of BRV, we must accommodate four key statistical issues: sample selection bias/truncation, disproportionate stratification, censoring, and unobserved heterogeneity. First, with regard to sample selection bias and truncation, we anticipate that the seller firm strategically selects the clients that are going to be used as references. The telecommunications firm selected 88 from a total of 5109 clients, and the financial services firm selected 94 from a total of 5576 clients as references. This sample selection problem results in a truncation problem because the only clients for which we can observe a value for BRV are those that are selected by the firm and agreed to be a reference. To accommodate this issue, our modeling framework must be able to uncover the drivers of reference client selection by the firm and accommodate this strategic selection bias from the drivers of BRV.[2] To accommodate the issue of selection bias, we implement a binary choice model to uncover the drivers of reference client selection. We then use the result of this estimation to correct for the sample selection bias (the cause of the truncation problem) found in the parameter estimates of the drivers of BRV.

Second, we face a problem pertaining to disproportionate stratification, given that such a small percentage of

[2]In this study, both firms already had established customer bases. However, if a new firm were to apply this framework and had only a few customers from which to choose, it would also be important to understand the type of potential client firm that is likely to be an early adopter because the goal of the seller firm is likely acceleration of diffusion.

FIGURE 2
A Timeline of the Data Collection



clients were selected for being a reference out of the total clients available to the firm. In this case, a little more than 1% for both the telecommunications firm (88 of 5109) and financial services (94 of 5576) firm were selected as references. To obtain insights into a firm's decision to select clients to be references, we want to maximize the sample variance in the dependent variable. To do so, we would ideally want an equal proportion of ones and zeros in the sample (Lancaster and Imbens 1991). However, it is also possible not to lose much information in the coefficients even when the split is 80/20 rather than 50/50 (Cramer, Franses, and Slagter 1999). Thus, to maintain a larger sample and still maximize the information from the data set, we disproportionately sample from the entire data set to create a sample with 20% of the clients that are references and 80% of the clients that are not used as references. We can then correct for the bias introduced by the disproportionate sample size straightforwardly by using a choice model with a traditional logit specification and an offset based on the disproportionate stratification (Donkers, Franses, and Verhoef 2003).

With regard to censoring, of the clients selected as references, the value of the BRV observed is greater than or equal to 0 (given that CLV was positive for new clients). This occurs because the prospects that adopt decide which client references influenced their decision to purchase. We observe a positive value for BRV only when at least one prospect found the reference valuable and 0 when no prospects indicated that a given reference was influential. To address this issue, we ran a censored regression model in which the dependent variable is the BRV score for the clients that were selected to be references and the value of BRV is censored at 0.

To account for the final modeling issue, unobserved heterogeneity, we ran a latent class censored regression model to determine the number of potential segments after we account for the variance through the focal variables of this study. For the full details on the sampling steps; selection, transformation, and censored regression equations; and the log-likelihood functions, see Appendix A. For details of the latent class segmentation, see Appendix B.

Measures

We need to identify a set of predictor variables to be used in our model of the drivers of reference client selection and BRV. For the selection equation, we include the two key factors the firm is likely to use to select clients to give references: (1) client firm size and (2) length of client relationship. For the BRV equation, we include the four key factors that may influence of the value of a client reference to the prospect along with the interaction effects and the selection bias correction: (1) client firm size, (2) length of client relationship, (3) reference media format, and (4) reference congruency. For the sake of simplicity and generalizability, we aggregated the data for each industry, for product/service category, and for functional area into seven categories to test congruency. (For a list of these categories, see Web Appendix W1 at www.marketingpower.com/jm_webappendix.) The following subsections discuss measurement of the four key drivers.

Client firm size. Research suggests that there are multiple measures of firm size that rely on both labor force and scale of operations (Kimberly 1976). Moreover, these measures may not always be highly correlated with one another. Thus, we operationalize client firm size on both the labor force dimension (number of employees) and the scale of operations dimension (annual revenue).

Length of client relationship. The length of the relationship between the client and the seller firm can be viewed as both the amount of time the relationship has existed and the expected time the relationship is likely to exist into the future. This suggests that both the length of time the alliance has existed (past relationship duration) and the depth of relationship (expected future relationship duration) between the client and seller firms are important factors in the measure of the length of client relationship (Gulati and Gargiulo 1999). To this end, we operationalize length of client relationship as both the length (tenure) and the depth (CLV) of the relationship between the seller and the client.

Reference media format. We measured reference media format using dummy variables coded by format type of the media used to provide the reference from the client firm to the potential client firm. These formats include video testimonial, audio testimonial, written testimonial, case study/white paper, and "call me" (an invitation to call the reference directly).

Reference congruency. Reference congruency depends on the degree of similarity between the referencing firm and the potential client firms that find the referencing client firm's reference value. Thus, we operationalized reference congruency as the ratio of potential client firms that found the reference valuable that were from the same industry, bought the same product or service, or had the same role within their organization as the total number of potential client firms that found the reference valuable. Table 2 provides details of the variables and their operationalizations.

Results

Overall Model Fit

Table 3 presents the parameter estimates along with the model fit statistics. We found that the full models (both the selection model and the latent class censored regression model) for each of the firms provided good overall fit (R^2 = .71 for the telecommunications firm, and R^2 = .68 for the financial services firm) with all variables being significant predictors of either client selection or BRV. In general, for the telecommunications firm, we find that together client firm size and length of client relationship (the two constructs based on client characteristics) explain approximately 31% of the variance of BRV, congruency explains approximately 17%, reference media format explains approximately 14%, and the interaction effects between client firm size and the other three constructs explain approximately 9%. We found similar results for the financial services firm. This suggests that references selected on the basis of the client characteristics alone (a potential benchmark model) explain approximately 31% of the vari-

TABLE 2
Variable Operationalization

Variable	Operationalization
Client Firm Size	
Employees	The number of employees in the referencing client
Revenue	The annual revenue of the referencing client (in millions of dollars)
Length of Client Relationship	
CLV	The customer lifetime value of the referencing client (in thousands of dollars)
Tenure	The time the referencing client has been a customer (years)
Reference Media Format	
Video testimonial	1 if the reference was a video file, 0 if not
Audio testimonial	1 if the reference was an audio file, 0 if not
Written testimonial	1 if the reference was a testimonial, 0 if not
Case study/white paper	1 if the reference was a case study/white paper, 0 if not
"Call me"[a]	1 if the reference was for a personal call, 0 if not
Reference Congruency	
Industry	(Number of converted prospects from the same industry that indicated this client's reference influenced their purchase)/(Number of converted prospects that indicated this client's reference influenced their purchase)
Product/service	(Number of converted prospects that purchased the same product/service that indicated this client's reference influenced their purchase)/(Number of converted prospects that indicated this client's reference influenced their purchase)
Role	(Number of converted clients whose decision maker was in the same role that indicated this client's reference influenced their purchase)/(Number of converted prospects that indicated this client's reference influenced their purchase)
Congruency	Average number of congruency matches for each converted prospect on three congruency factors from prospects that indicated this client's reference influenced their purchase
Interaction Effects[b]	
Firm size × relationship length	Client firm size × length of client relationship
Firm size × reference media format	Client firm size × reference media format
Firm size × congruency	Client firm size × congruency

[a]We do not include "call me" in the regression because each of the references must be categorized into one of the five categories listed, and using all five would cause perfect multicollinearity.
[b]For the interaction effects, "client firm size" is represented by the revenue variable. We found similar results when we used employees. "Length of client relationship" is represented by tenure. We found similar results when we used CLV. "Reference media format" was computed as follows: It is ordered from 5 to 1 according to the richness of the media used for the reference (video = 5, audio = 4, written = 3, case study/white paper = 2, and "call me" = 1). "Congruency" is represented by the congruency variable.

ance of BRV. By selecting references according to fit (congruency) and reference media format, and taking into account the synergistic value of client firm size, the additional variance of BRV that the model explains is approximately 40%.

From the results of the latent class analysis, we found that there is only one latent segment for our model; thus, we only report the results for the single-segment censored regression model. (For the results of the null models, along with the full model, for the financial services firm, see Web Appendix W2 at www.marketingpower.com/jm_webappendix; note that we found similar results for the telecommunications firm.) In addition, the parameter estimates from the models provide several key insights into the effect of each variable on the BRV for each of the referencing clients.

Selection Model

Client firm size. For client firm size in the selection model, we found that the number of employees has a positive effect on selection for both the telecommunications firm (.062, $p < .01$) and the financial services firm (.076, $p = .02$). This finding suggests that larger clients are more likely to be selected to provide a reference. In addition, we found that revenue has a positive effect on selection for both the telecommunications firm (.00026, $p < .01$) and the financial services firm (.00046, $p = .02$). This suggests that the larger a client's own revenue, the more likely a client will be selected to provide a reference. These findings support H_{1a}, that the seller firm is more likely to select larger clients, in terms of both labor force and scale of operations, as a reference.

Length of client relationship. For length of client relationship in the selection model, first, we found that CLV has an inverted U-shaped effect on selection for both the telecommunications firm (for CLV: .102, $p < .01$; for CLV^2: –.00024, $p = .02$) and the financial services firm (for CLV: .124, $p < .01$; for CLV^2: –.0003, $p = .01$). This suggests that, first, the firm is more likely to select referencing clients that provide more profit and are more likely to have a longer relationship duration, to a threshold. Second, we find that tenure has a positive effect on client selection for both the telecommunications firm (.163; $p < .01$) and the financial services firm (.149; $p = .02$). This suggests that the seller

TABLE 3
Parameter Estimates

Variable	Telecommunications (SD)		Financial Services (SD)	
A: Selection Model				
Intercept	.18	(.049)	.11	(.041)
Client Firm Size				
Number of employees	.062	(.021)	.076	(.032)
Annual revenue	.00026	(.0001)	.00046	(.0002)
Length of Client Relationship				
CLV	.102	(.028)	.124	(.044)
$(CLV)^2$	–.00024	(.0001)	–.0003	(.00012)
Tenure	.163	(.056)	.149	(.063)
B: BRV Model				
Intercept	3.14	(1.06)	3.04	(1.06)
Client Firm Size				
Number of employees	.231	(.082)	.201	(.082)
Annual revenue	.0086	(.003)	.019	(.0063)
Length of Client Relationship				
CLV	.339	(.052)	.409	(.052)
$(CLV)^2$	–.0072	(.002)	–.0076	(.0015)
Tenure	.471	(.091)	.394	(.082)
Reference Media Format				
Video testimonial	.256	(.042)	.308	(.059)
Audio testimonial	.204	(.033)	.246	(.047)
Written testimonial	.176	(.057)	.208	(.042)
Case study/white paper	.112	(.038)	.141	(.056)
Reference Congruency				
Industry	.464	(.087)	.374	(.066)
Product/service	.626	(.144)	.521	(.142)
Role	.291	(.083)	.238	(.098)
Interaction Effects				
Firm size × relationship length	.004	(.0016)	.008	(.0027)
Firm size × reference media format	.0027	(.0008)	.006	(.0022)
Firm size × congruency	.0052	(.0017)	.0081	(.0024)
Sample Selection Correction				
Lambda (λ)	.42	(.109)	.41	(.118)
Model Fit				
R^2	.71		.68	
Log-likelihood	–178.61		–169.42	
AIC	417.81		401.4	

Notes: All variables in the model are significant at $p < .05$.

firm is more likely to select clients that have had a longer prior relationship as a reference. In general, these findings support H_{2a}, which predicts that, to a threshold, seller firms are more likely to select clients that have had and are expected to have longer relationships with the seller firm as a reference.

Summary. In general, all these variables and the significance of the parameter estimates suggest that the firm does not randomly select the clients that provide references. Instead, the firm is probably selecting larger clients with stronger relationships with the seller firm (to a threshold). This finding is also supported by the positive and significant coefficient on the pseudo inverse Mills ratio for both the telecommunications firm (.42, $p < 0.01$) and the financial services firm (.41, $p < .01$), further validating the need to accommodate for this selection bias.

Censored Regression (BRV Model)

Client firm size. We found that both variables that describe the client firm size of the referencing client for the telecommunications firm (for employees: .231, $p < .01$; for revenue: .0086, $p < .01$) and the financial services firm (for employees: .201, $p < .01$; for revenue: .019, $p < .01$) are positive and significant, in support of H_{1b}. “This finding suggests that prospects are more likely to value references from clients that are larger, in terms of either labor force or scale of operations.

Length of client relationship. For length of client relationship, we found that CLV had an inverted U-shaped relationship for both the telecommunications firm (for CLV: .339, $p < .01$; for CLV^2: –.0072, $p < .01$) and the financial services firm (for CLV: .409, $p < .01$; for CLV^2: –.0076, $p <$

.01). We also found that tenure has a positive relationship for both the telecommunications (.471, $p < .01$) and financial services (.394, $p < .01$) firms. In this case, the longer the client has been purchasing from the firm and the greater the likelihood of a longer future relationship duration, the greater was the influence of the reference from that client on a prospect's decision to adopt. In general, these findings support H_{2b}, suggesting that longer relationships between clients and the seller firm (to a threshold) lead to a higher BRV.

Reference media format. For all reference media format variables, we found a positive relationship for both firms. The specific values are as follows: for the video testimonial variable, telecommunications: .256, $p < .01$; financial services: .308, $p < .01$; for the audio testimonial variable, telecommunications: .204, $p < .01$; financial services: .246, $p < .01$; for the written testimonial variable, telecommunications: .176, $p < 0.01$; financial services: .208, $p < 0.01$; and for case study/white paper variable, telecommunications: .112, $p < .01$; financial services: .141, $p = .02$.

We ordered the five reference media format variables according to the size of the parameter estimates from highest to lowest: (1) video testimonial, (2) audio testimonial, (3) written testimonial, (4) case study/white paper, and (5) "call me."[3] In addition, we tested to determine whether there is a significant difference between the levels of each of the parameter estimates using a pairwise t-test. We found that in both firms, the parameter estimate for video testimonial is statistically significantly larger than the parameter estimate for audio testimonial (for telecommunications: t = 9.12, $p < .01$; for financial services: t = 7.95, $p < .01$). We found that in both firms, the parameter estimate for audio testimonial is statistically significantly larger than the parameter estimate for written testimonial (for financial services: t = 4.00, $p < .01$; for telecommunications for financial services: t = 5.85, $p < .01$). For both cases, we found that the parameter estimate for written testimonial is statistically significantly larger than the parameter estimate for case study/white paper (for telecommunications: t = 8.77, $p < .01$; for financial services: t = 9.31, $p < .01$). For both cases, we found the parameter estimate for case study/white paper is statistically significant, meaning it is larger than the value added by "call me," which can be found in the intercept (for telecommunications: t = 2.96, $p < .01$; for financial services: t = 2.87, $p < .01$). In general, this finding supports H_3, suggesting that client references with richer media content tend to influence prospects more than references with less rich content.

Reference congruency. For the industry congruency variable, we found a positive relationship for both the telecommunications (.464, $p < .01$) and financial services (.374, $p < .01$) firms. This suggests that as the number of prospects in the same industry as the referencing client increases, so does the BRV of that referencing client. For the product congruency variable, we found a positive relationship for both the telecommunications (.626, $p < .01$) and financial services (.521, $p < .01$) firms. This suggests that as the percentage of prospects that valued the reference and purchased the same product or service increased, the BRV of the referencing client increased. For the role congruency variable, we found a positive relationship for both the telecommunications (.291, $p < .01$) and financial services (.238, $p = .02$) firms. This suggests that as the percentage of prospects that valued the reference and held the same role as the person in the referencing client increased, the BRV of the referencing client increased.

Our findings suggest that increasing the opportunities for congruency can add significant value to a client's reference (e.g., through strategically having a broad set of references from which to choose). However, the type of congruency can add differing levels of value. We find that for both firms, the value provided by different reference congruencies follows the same order in terms of importance: Product/service congruency is the most valuable (when compared with industry congruency, for the telecommunications firm: t = 9.05, $p < .01$; for the financial services firm: t = 9.07, $p < .01$); industry congruency is the second most valuable (when compared with role congruency, for the telecommunications firm: t = 13.52, $p < .01$; for the financial services firm: t = 11.15, $p < .01$); and role congruency is the third most valuable in terms of BRV. Thus, if a prospect is interested in a reference, although all congruencies are important, the most influential references will be product/service related first, industry related second, and role related third. The finding that product/service and industry (i.e. market) are the most important congruency factors supports the management literature that focuses on product–market fit as a surrogate for congruency (Alderson 1965).

Interaction effects. We found each of the interaction terms to be positive and significant for both the firms. For client firm size × length of client relationship, we found a coefficient of .004 ($p = .02$) for the telecommunications firm and .0008 ($p < .01$) for the financial services firm. For client firm size × reference media format, we found a coefficient of .0027 ($p < .01$) for the telecommunications firm and .006 ($p = .01$) for the financial services firm. For client firm size × reference congruency, we found a coefficient of .0052 ($p < .01$) for the telecommunications firm and .0081 ($p < .01$) for the financial services firm. These findings support H_{5a}–H_{5c}, suggesting that larger client firms have a synergistic and positive effect on the value of the reference across the other constructs.

Summary. In general, all these variables and the significance of the parameter estimates suggest that we have uncovered many of the drivers of BRV, or the level of influence a given reference will have on getting a prospect to adopt. Thus, when accounting for the potential of selection bias, seller firms can now determine which references in their client reference database are likely to be the most valuable in a given sales situation.

[3]First, we omitted "call me" from the regression and treated it as the base category for comparison. Second, it could be the case that simply providing a client list offers some value. Because all the references were provided in each sales situation, we cannot directly control for simply being on the client list in this context.

Does High BRV = High CLV?

A key finding from Kumar, Petersen, and Leone (2007, 2010) is that individual customers with the highest customer referral value (CRV) are not the same customers as those with the highest CLV. Thus, it is important to manage customers on both their CLV and their CRV scores. In the case of BRV, it is also important to determine whether clients that have a high CLV are the same as those that provide the most valuable references. To do this, we ordered the client reference firms from the telecommunications and financial services firms that were part of the field test by their realized CLV during the three years at the beginning of the field test. We divided these clients into ten deciles and computed the average CLV and BRV for each decile. Table 4 presents the results.

Table 4 shows that, similar to the findings regarding CRV, the clients with the highest BRV are not the same as the clients with the highest CLV. For both firms, the clients with the highest BRV fall into the third, fourth, and fifth deciles on CLV (fifth having the highest BRV in both firms). We observe that referencing clients in the first two deciles (highest CLV) are also higher on BRV compared with the clients in the lowest four deciles (seventh through tenth), which have by far the lowest average BRV.

When comparing CLV with CRV, Kumar, Petersen, and Leone (2007, 2010) find that the customers with the highest CLV did not have a relatively high CRV. This was possibly the case because of the incentives provided to encourage referral behavior. Customers with the highest CLV probably did not value the referral incentive to the degree that the medium CLV customers did. In this case, there is no incentive, and the BRV of the clients in the top deciles is still relatively high. The highest deciles still have a high BRV because of client firm size (i.e., higher client firm size → higher BRV). However, the medium CLV clients that give references have the highest BRV due to the length of client relationship (i.e., medium relationship duration → higher BRV) and the congruency effect (higher congruency → higher BRV). With regard to congruency, we found that many of the prospects being targeted for acquisition had the most in common with the customers in the medium CLV group.

We also observe that the average BRV scores in Deciles 1–6 for the telecommunications firm and Deciles 1–7 for the financial services firm are higher than the average CLV scores for the clients in those deciles. This suggests that getting a medium- to high-value business client to provide a reference can be potentially much more profitable than merely focusing on cross- and up-selling opportunities to that business client. To provide some additional insights into the type of clients that provide high- versus low-value references, we segmented the referencing clients using a median split of BRV (see Table 5).

Table 5 shows significant differences between the profiles of clients that are high on BRV for both firms. As we expected, the CLV of the high-BRV clients is much higher than that for the low-BRV clients (for the telecommunications firm, 18,400 vs. 5800; for the financial services firm, 18,700 vs. 5200). We observe a significant difference in the tenure between the two groups: Clients that have a higher BRV have longer tenure (for the telecommunications firm,

TABLE 4
Decile Analysis for BRV and CLV

	Telecommunications (n = 9 for All but Tenth Decile)		Financial Services (n = 9 for All but Tenth Decile)	
Decile	CLV (in Thousands)	BRV (in Thousands)	CLV (in Thousands)	BRV (in Thousands)
1	30.8	34.6	26.2	31.2
2	25.7	40.8	23.6	33.6
3	20.2	49.6	20.5	41.8
4	17.3	55.8	18.1	59.2
5	14.9	61.2	15.7	66.8
6	12.1	30.2	12.8	36.1
7	9.3	6.2	9.6	10.2
8	6.4	3.1	5.5	4.1
9	3.2	1.8	2.9	2.2
10	.8	.2	.4	.18

TABLE 5
Segment Description for High and Low BRV Clients

	Telecommunications		Financial Services	
Variable	High BRV (n = 44)	Low BRV (n = 44)	High BRV (n = 47)	Low BRV (n = 47)
Average CLV (in thousands)	18.4	5.8	18.7	5.2
Average tenure (years)	10.3	4.9	14.7	6.8
Most common media format	Video	“Call me”	Video	“Call me”
Average number of employees	2710	468	2158	318
Average annual revenue (in millions of dollars)	59.4	11.2	70.6	18.8

10.3 years vs. 4.9 years; for the financial services firm, 14.7 years vs. 6.8 years). We observe that the clients that have high BRV are more likely to have provided a video reference than a "call me" reference for both the telecommunications and financial services firms. Finally, in terms of firm size, the average number of employees (for the telecommunications firm, 2710 vs. 468; for the financial services firm, 2158 vs. 318) and the average annual revenue (for the telecommunications firm, $59.4 million vs. $11.2 million; for the financial services firm, $70.6 million vs. $18.8 million) are higher for the high BRV clients than for the low BRV clients. The results from this profile analysis add more support to the endogenous decision the firm is already making with regard to selecting clients for references that generally have a higher CLV, longer tenure, larger employee bases, and higher annual revenues. In addition, it suggests that in the future, the selection of the clients can be even more targeted to the prospects to increase the probability of customer acquisition and the CLV of converted prospects.

The Impact of Ref_n, DOI_{in}, and CLV_n on BRV

Our findings show that using client references can add significant value to the new customer acquisition process. It is also important to understand, at least in a general sense, the relative impact of each of the three components on BRV. For example, do clients with a high BRV influence the small number of prospects to a great extent (i.e., high Ref_n and DOI_{in} for a given client i with a small frequency of n)? Alternatively, do clients with a high BRV provide a small amount of influence on a large number of prospects (i.e., low Ref_n and DOI_{in} for a given client i with a large frequency of n)? First, we want to know how well the three determinants of BRV are correlated (see Table 6).

Table 6 indicates that Ref_n, DOI_{in}, and CLV_i are positive but weakly correlated. The only significant correlation ($p < .10$) is between Ref_n and CLV_i (r = .16). This suggests that newly acquired client firms that are ultimately the most profitable are more likely to find references more influential in their adoption than less profitable newly acquired client firms. However, these results show that, in general, the three determinants of BRV are uncorrelated.

To understand how references in general affect the decision of a prospect to adopt, we investigate the means and standard deviations of Ref_n across all converted prospects for the financial services ($\mu(Ref_n) = 55$ and $\sigma(Ref_n) = 19$) and telecommunications ($\mu(Ref_n) = 62$ and $\sigma(Ref_n) = 17$) firms. These results suggest that client references play a key role in the purchase decisions of prospects for both the financial services and telecommunications firms, with, on average, more than 50% of the purchase influence resulting from the client references. Although at first glance, the influence of client references may seem high, this finding is not surprising given some recent evidence in the marketplace. First, a recent report found that more than 90% of survey respondents stated that the demand for business references was higher in 2007 than in 2006 (Wood 2007). Additional evidence indicates that for three customer reference programs at technology firms, references played an important role for customer acquisition efforts by both the marketing and sales departments (Godes 2008). Thus, while traditional marketing and sales force efforts continue to be relevant to customer acquisition, references from current business customers are playing an increasingly prominent role in influencing new customer adoption. This means that it is necessary in most cases not only to develop a usable business reference program but also to identify which clients have the potential to bring value in customer acquisition efforts.

TABLE 6
Correlation Between Ref_n, DOI_{in}, and CLV_i

	Ref_n	DOI_{in}	CLV_i
Ref_n	1		
DOI_{in}	.12	1	
CLV_i	.16*	.08	1

*Denotes significance at $p < .10$. (All other pairwise correlations are not significant.)

To shed light on whether prospects value many different client references more than only a few or one key client reference, we investigated the mean number of client references for each converted prospect that had $DOI_{in} > 0$ for both the financial services (μ(number of references per newly acquired customer with positive influence [$DOI_{in} > 0$]) = 2.1 and $\sigma = .5$) and telecommunications (μ(number of references per newly acquired customer with positive influence [$DOI_{in} > 0$]) = 1.5 and $\sigma = .4$) firms. This finding shows that, on average, converted prospects use one or two clients as key references to influence their decision to adopt. However, the particular references selected in each case vary widely across the set of converted prospects. Again, this finding is not necessarily surprising given the empirical results of this study. For example, we found that reference congruency played an important role in a referencing client's BRV score. This means that prospects put more weight on client references that match with their situation, whether it is based on industry, product/service, or role congruency. Given that only a few clients have high congruency in each new customer acquisition setting, it makes sense that, on average, only a few client references mattered in influencing prospect adoption. In addition, it shows the importance of having a variety of references from clients in different industries that purchase different products and services and from people from different functional areas within the client's firm; this variety is necessary to increase the probability that reference congruency can be achieved for a prospect.

Finally, to understand what proportion of the value generated by prospects through their CLV was being attributed to BRV, we investigated the mean and standard deviation of CLV for all the converted prospects for the financial services ($\mu[CLV_n] = \$14,064$ and $\sigma[CLV_n] = \$5,818$) and the telecommunications firm ($\mu[CLV_n] = \$15,469$ and $\sigma[CLV_n] = \$7,963$). This finding shows that, on average, the converted prospects that joined during the one-year time period of the field study were profitable customers for the financial services and telecommunications firms. If we compare the mean values with those in Table 5 (i.e., the mean CLVs of the referencing clients), we find that, on average, the converted prospects have a slightly lower CLV than the high-BRV referencing clients but have a much higher CLV than the low-BRV referencing clients for both firms. This suggests that business reference programs can be successful in attracting profitable customers, some of which could serve as successful referencing clients in the future, a potential topic for further research.

Implications

This research yields several key implications for both the marketing literature and practice. First, we introduce the concept of BRV. Here, we define BRV as the ability of a client's reference to provide value to the seller firm and the degree to which it does so by influencing a prospect to adopt. We show that there are three components of BRV: (1) the influence that all client references have on newly acquired customers compared with other forms of marketing, (2) the influence each specific client reference has on converted prospects, and (3) the profitability of the converted prospects. We also demonstrate how a firm can compute BRV using a straightforward three-step process that retrospectively reports a measure of reference value. The process requires two items: (1) a survey of the newly acquired customers at the time of adoption and (2) a measure of the profitability of the newly acquired customers.[4]

Second, we identify and empirically test the drivers of BRV. Identifying the key drivers is critical to select the best clients to serve as references and also to understand how best to deliver the reference message (format). We show that there are four key drivers of BRV: (1) client firm size, (2) length of client relationship, (3) reference media format, and (4) reference congruency. We find that the source of the reference matters, in terms of both firm size and length of relationship. Thus, it is important that managers select the right clients to use as references. We also find that the reference media format is an important driver of BRV, such that richer media formats are more influential. Importantly, we found that all the reference format variables have a larger effect than the "call me" approach, indicating that it is worthwhile to provide even a single client reference beyond simply offering the opportunity to call a current client; this type of reference contains no immediate value to the prospect. In addition, we observed through our qualitative interviews that managers often do not believe they have the time to connect with other managers, which offers some additional external validity to these findings. We find that reference congruency significantly increases BRV. Thus, it is important when possible to match clients with prospects that purchase the same product or service (highest effect size), are in the same industry (second highest effect size), and/or have the same role/position within their firm (third highest effect size). Finally, we find that when larger clients also have a longer relationship with the seller firm, a reference in a richer media format, and/or are more congruent with the prospect the reference has the ability to provide an incrementally larger degree of adoption influence—suggesting that larger client firms add direct and indirect value to social influence.

A third key contribution of this study is in shedding light on the impact of Ref_n, DOI_{in}, and CLV_n on BRV. Our findings from this additional analysis can provide insights to firms that aim not only to begin but also to run successful business reference programs. We show that client references play an ever-increasing role in the decision for a prospect to adopt, making it necessary to have a catalog of client references ready for the sales team to use during the sales process. However, we show that usually only a few client references seem to play a key role in influencing prospects to adopt and that the key client references varied significantly across converted prospects. This suggests that sellers should have a portfolio of client references, including clients with varied characteristics, to match the client to the prospect successfully and that it might be more effective to bring in only a limited set of "targeted" references in the sales process. Finally, we show that running a successful business reference program can help in converting prospects to clients that are profitable to the firm.

Limitations and Further Research

We should point out a few limitations and research opportunities to consider when measuring BRV and attempting to implement a successful reference program. First, we measured BRV for only two firms. While there is a significant number of other firms in these industries that could benefit from this study, client references may not be a key driver of customer acquisition in some industries, or the drivers of reference value may vary in their importance from this context. For example, in more complex selling environments (e.g., marketing and consulting projects, firms selling customized industrial goods and solutions), specific project, rather than product, attributes or degree of project success (e.g., 15% return on investment) may be most relevant.[5] In addition, other variables such as prior product or category experience might help explain the difference the value of a reference can have when prospects have low versus high product knowledge. Further research should test this framework by including potential additional drivers in other industries and general contexts (e.g., business to consumer) to determine its generalizability.

The method we use to track the influence of client references is retrospective and requires the converted prospect to evaluate the impact the client reference had on their decision to adopt. There may be a difference between the true impact of the reference and the self-reported impact for any number of reasons. For example, if the sales cycle is extremely long and the client references were introduced at

[4]Although there are other methods that could be used to survey customers, such as self-explicated conjoint analysis, we believe that our method provides a simple and straightforward method to obtain an accurate value for BRV.

[5]We thank one of the anonymous reviewers for providing this comment.

the beginning of the sales process (and not again later), it may be difficult for the converted prospect to remember which references influenced them or if client references mattered at all. In some cases, converted prospects may not remember the client reference and give it no value, when it may be that the client reference was what brought the salesperson to the door in the first place (making it critical to the acquisition). Moreover, although we have no evidence to suggest a problem, it might be the case that even if the client can remember the reference, the client may be unable to accurately report what influences the references had on their decisions and the weights to put on the different references. This is a problem with many studies that use self-report measures. Further research could attempt to measure BRV as a function of observed variables to alleviate this problem.

The operationalization of the four key constructs (client firm size, length of client relationship, reference media format, and congruency) can be measured in several alternative ways. For example, constructs such as client firm size and length of relationship could be construed as client reputation and client embeddedness, respectively. While the operationalizations for the four key constructs we used in this study were theoretically driven, further research could add to their richness in the reference value literature by testing alternative measures that capture more of the dimensions of the key constructs.

Furthermore, the client may feel obligated to find value in the references (e.g., social desirability bias) given that the survey involves the influence of client references (Fisher 1993). In the current study, the sales cycles for the telecommunications and financial services firms were fairly short, on the order of a few months at most, and many of the decision makers from the firm suggested that references were often used in the final decision-making process, likely lessening the potential bias present in the self-report client reference influence measure.

It is possible that a client firm could be a good reference on many dimensions (e.g., larger, moderate relationship duration, high degree of congruency), but the product or service the seller firm offers is not appropriate for the prospect.[6] In this case, the low product or service fit with the potential client might overstate the unconditional impact of the reference. Although the data we collected in this study cannot directly address this issue, it would be a worthwhile topic for further research.

Finally, we allowed all prospects to access all the client references during the entire sales process. The results of this study indicate, for example, that reference congruency plays a major role in influencing prospect adoption. Further research, which would help validate the findings of Hada, Grewal, and Lilien (2011), could determine whether targeting specific prospects with a limited set of client references would have a greater impact on prospect adoption by removing the cluttering effect of many undesirable or ineffective references. Further research could consider how different reference sets at different times during the adoption process might have different levels of influence. This might also help validate recent survey findings, which suggest that different reference content might be influential at different times during the selling cycle (Godes 2008).

[6]We thank one of the anonymous reviewers for raising this potential issue.

Appendix A
Details on the Sampling, Equations, and Log-Likelihood Function

To show how the models are developed, we can begin with the standard logit model:

$$\text{(A1)} \qquad P(z_i = 1 | w_i) = \frac{\exp(w_i'\gamma)}{1 + \exp(w_i'\gamma)}.$$

In this case, z_i is 1 when selected and 0 otherwise, w_i is a set of explanatory variables, and γ is a vector of parameter estimates. Next, we need to correct for the outcome-dependent disproportionate stratified sampling. We do this by including the probability that a given observation comes from one of the two different strata—in this case, either those selected (1) or those not selected (0) to be a reference. Similar to Donkers, Franses, and Verhoef (2003), we create two new parameters u_{s0} and u_{s1}. In this case, u_{sk} represents the percentage of stratum k, which was selected into the sample, where $u_{sk} = n_{sk}/N_{sk}$, where n_{sk} is the number selected from the stratum and N_{sk} is the total population of the stratum. The result is the following pseudolikelihood:

$$\text{(A2)} \quad P(z_i = 1 | w_i, \text{stratum}_k = s) = \frac{\exp\left[w_i'\gamma + \ln\left(\frac{u_{s1}}{u_{s0}}\right)\right]}{1 + \exp\left[w_i'\gamma + \ln\left(\frac{u_{s1}}{u_{s0}}\right)\right]}.$$

Thus, we obtain the pseudolikelihood of the logit model by adding a correction of $\ln(u_{s1}/u_{s0})$ to offset $w'_{i\gamma}$ for each observation. This can easily be accomplished in most statistical software packages by offsetting the intercept estimate of the standard logit model.

To accommodate these issues simultaneously, we develop a two-stage modeling framework with pseudo logit-ordinary least squares (OLS) specification. We implement this two-stage framework in a similar way to the well-known Heckman two-stage model with one exception: We do not use a probit model specification in Stage 1. We instead chose to use a logit model specification,because the correction for disproportionate sampling is straightforward. Then, to link the logit model with the OLS model, we use a generalized econometric method as Lee (1983) describes.

We can implement this model in the same way as the Heckman two-stage model with only a few minor modifications. Specifically, we use the pseudo logit model in place of the usual probit model, and we compute a pseudo inverse Mills ratio using the output of the pseudo logit model using the following three steps.

1. We estimate the logit model with the offset correction for disproportionate stratification.
2. We compute the pseudo inverse Mills ratio (λ^*) using the following equation:

$$\lambda^* = \frac{\phi\left\{\Phi^{-1}\left[F(w_i'\gamma)\right]\right\}}{F(w_i'\gamma)},$$

where ϕ is the normal density function and $F(\cdot)$ is the logit distribution function.
3. We run a censored regression and include the pseudo inverse Mills ratio (λ^*) as an additional variable.[7]

First, we select samples from the two strata that will be used in our two-stage modeling framework. We select samples for the ones (reference clients) and zeros (nonreference clients) that generate an 80/20 distribution of zeros to ones. This results in a sample size of 440 (88 ones and 352 zeros) for the telecommunications firm and 470 (88 ones and 376 zeros) for the financial services firm. In this case, the ones represent 100% of the total stratum population, and the zeros represent a random sample of approximately 7% of the stratum population for both the telecommunications and financial services firms. We ran the models multiple times with different random samples from the zeros and found no significant differences in the model results for either of the firms. We then use the following equations for our modeling framework:

Selection Equation:

$$\text{(A3)}\qquad z_i^* = w_i'\gamma + u_i$$

$$z_i = \begin{cases} 1 \text{ if } z_i^* > 0 \\ 0 \text{ if } z_i^* \le 0 \end{cases}.$$

Censored Regression Equation:

$$\text{(A4)}\qquad y_i^* = x_i'\beta + e_i, \text{ if } z_i = 1; \text{ and}$$

$$y_i = \begin{cases} y_i^* \text{ if } y_i^* > 0 \\ 0 \quad \text{if } y_i^* \le 0 \end{cases}.$$

Transformation Equation:

$$\text{(A5)}\qquad u_i^* = J_1(u_i) = \Phi^{-1}\left[F(u_i)\right].$$

In these equations, u_i^* and e_i are bivariate normal with means of 0, standard deviations of 1 and σ, and correlation of ρ, where $F(u_i)$ is the pseudo logit model specification as described previously. In addition, z is the selection variable, where if $z_i = 1$ the client was chosen to be a reference and if $z_i = 0$ the client was not chosen to be a reference. Finally, y_i is only observed when $z_i = 1$ and y_i is censored at 0—where $BRV_i = y_i$. The resulting log-likelihood function must accommodate the selection/truncation, disproportionate stratification, and censoring issue. As Maddala (1983) notes, we get the following log-likelihood function:

[7]Given that the results of the latent class segmentation suggested one segment, we do not discuss the integration of the latent class segmentation in our model estimation steps here. For a discussion of the latent class segmentation, see Appendix B.

$$\text{(A6)}\qquad LL = \sum_{\{i|z_i=0\}} \left\{\ln\left[1 - F(w_i'\gamma)\right]\right\}$$

$$+ \sum_{\{i|z_i=1,\, y_i=y_i^*\}} \left\{\ln\left[\phi\left(\frac{y_i - x_i'\beta}{\sigma}\right)\right] - \ln\sigma\right.$$

$$\left. + \ln\left(\Phi\left\{\frac{\Phi^{-1}\left[F(w_i'\gamma)\right] + \rho\left(\frac{y_i - x_i'\beta}{\sigma}\right)}{\sqrt{1-\rho^2}}\right\}\right)\right\}$$

$$+ \sum_{i|z_i=1,\, y_i=0} \left\{\ln \int_{-\infty}^{\frac{-x_i'\beta}{\sigma}} \int_{-w_i'\gamma}^{\infty} \phi_2(u, v, \rho)\, du\, dv\right\}.$$

Appendix B
Latent Class Segmentation

The purpose of the latent class segmentation is to uncover whether there are multiple homogeneous segments of client references in the portfolio of references for the telecommunications or financial services firms. To determine if multiple segments are present, we use the method Jedidi, Ramaswamy, and DeSarbo (1993) developed.

We carry out the latent class segmentation of clients by setting the number of segments to different numbers and then determining which segmentation scheme provides the best results based on the consistent Akaike information criterion (CAIC). We found the following results for the financial services firm[8]:

Number of Segments	Log-Likelihood	CAIC
1	–169.42	416.26
2	–166.03	491.45
3	–162.71	566.78
4	–159.46	642.25

Given that the CAIC is lowest for the one-segment solution, we chose that as the optimal number of segments (Jedidi, Ramaswami, and DeSarbo 1993), where the CAIC is an alternative criteria to the AIC that corrects for the overestimation bias in AIC by penalizing for overparameterization. It is defined as follows:

$$CAIC_m = -2 \times \ln\left[L(Q|m)\right] + N_m(\ln I + 1),$$

where

$L(Q|m)$ = The likelihood of the model given segment m,
N_m = The effective number of parameters estimated in an m-class solution, and
I = The number of observations in the sample.

A one-segment solution means that there is no significant benefit to segmenting clients into multiple latent segments. However, a one segment solution does not mean that

[8]We find similar results for the telecommunications firm.

there is no variation between segments. It only means that the additional variance explained by dividing customers into multiple segments is outweighed by the reduction in parsimony from the use of too many parameters. In addition, it also suggests that the variables used in the censored regression model explained much of the heterogeneity among clients used for references.

The parameter estimates for each of the four latent class estimations (one, two, three, and four segments) only showed some slight differences between each of the segments—both in magnitude and significance.[9] However, in no cases did we observe the signs of the parameter estimates change. As a result, the slight, but not significant, increases in variance explained when each subsequent segment is added leads to the one-segment solution having the lowest CAIC, likely because the sample size is small (94 for the financial services firm) relative to the number of variables in the model that need to be estimated (17).

[9]Parameter estimates for the two-, three-, and four-segment solutions are available on request.

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