

# Dynamic Relationship Marketing

Firms routinely engage in relationship marketing (RM) efforts to improve their relationships with business partners, and extant research has documented the effectiveness of various RM strategies. According to the perspective proposed in this article, as customers migrate through different relationship states over time, not all RM strategies are equally effective, so it is possible to identify the most effective RM strategies given customers' states. The authors apply a multivariate hidden Markov model to a six-year longitudinal data set of 552 business-to-business relationships maintained by a *Fortune* 500 firm. The analysis identifies four latent buyer–seller relationship states, according to each customer's level of commitment, trust, dependence, and relational norms, and it parsimoniously captures customers' migration across relationship states through three positive (exploration, endowment, recovery) and two negative (neglect, betrayal) migration mechanisms. The most effective RM strategies across migration paths can help firms promote customer migration to higher performance states and prevent deterioration to poorer ones. A counterfactual elasticity analysis compares the relative importance of different migration strategies at various relationship stages. This research thus moves beyond extant RM literature by focusing on the differential effectiveness of RM strategies across relationship states, and it provides managerial guidance regarding efficient, dynamic resource allocations.

**Keywords:** hidden Markov models, relationship marketing

**Online Supplement:** <http://dx.doi.org/10.1509/jm.15.0066>

Understanding and managing customer relationships is fundamental to marketing. Accordingly, firms spend in excess of \$12 billion annually on customer relationship management, in efforts to understand how to target and sell to customers across various relationship stages (Gartner Research 2013). Substantial research in the relationship marketing (RM) domain also has proposed multiple relational constructs and frameworks to better understand the nature of the buyer–seller relationship (Mullins et al. 2014; Samaha, Beck, and Palmatier 2014). Yet much of this literature treats relationships as temporally homogeneous, implying that all relationships respond in similar ways to RM initiatives, independent of the relationship stages or states. More recent research using hidden Markov models (HMMs) has instead suggested the importance of acknowledging customer relationship states as a means to understand customer behavior, such that certain marketing actions might be more effective in some states than in others (Luo and Kumar 2013; Netzer, Lattin, and Srinivasan 2008). This concept is particularly important in business-to-business (B2B) settings, wherein customer relationships take longer to develop, last longer, exhibit higher switching costs, and have greater impacts on outcomes than in business-to-consumer settings (Zhang, Netzer, and Ansari 2014). Relationships are dynamic in nature, and as customers move across relationship

states, certain RM strategies might be more effective than others or even represent a waste of resources in some situations.

Yet very little research has explained how different RM strategies vary in their effectiveness for moving customers across different relationship states and enhancing performance through state migrations. To fill this gap and contribute to RM literature, we adopt a dynamic relationship marketing framework to investigate the effectiveness of various RM strategies across different states (stages). Specifically, we ask the following question: Given a customer's current relationship state, what is the most effective RM strategy to migrate it to a higher performing relationship state or prevent it from moving to a lower performance state? We test the most commonly used RM strategies across different customer relationship states to evaluate their effectiveness.

Prior theoretical research has acknowledged that buyer–seller relationships evolve through distinct stages that exhibit different relational construct levels and varied performance (Celuch, Bantham, and Kasouf 2006; Dwyer, Schurr, and Oh 1987; Jap and Ganesan 2000). Literature also has identified RM constructs that act as antecedents to relationship development and thus serve as migration strategies (Palmatier et al. 2006). Empirical research in B2B relationships has often used survey data to illuminate relationship constructs, investigating one construct at time or examining cross-sectional contexts. Empirical research has noted the flexibility of HMMs to uncover latent relationship states from observed customer behaviors (Luo and Kumar 2013; Netzer, Lattin, and Srinivasan 2008). These models are useful for studying relationships in a dynamic setting, because they describe the latent relationship according to discrete states at any given point in time, uncover customer migration patterns across states, and identify the variables responsible for migrations.

Although the use of HMMs has greatly advanced knowledge of customer relationships, most studies have used customer

---

Jonathan Z. Zhang is Assistant Professor of Marketing, University of Washington (e-mail: zaozao@uw.edu). George F. Watson IV is Assistant Professor of Marketing, Colorado State University (e-mail: george.watson@colostate.edu). Robert W. Palmatier is Professor of Marketing, University of Washington (e-mail: palmatrw@uw.edu). Rajiv P. Dant is Professor of Marketing, University of Oklahoma (e-mail: rdant@ou.edu). The authors thank the Marketing Science Institute for their comments on an early version of this manuscript as part of their Working Paper Series. Werner Reinartz served as area editor for this article.

transactional data to infer underlying relational constructs or mechanisms, such that they are not very “theory-rich.” In response, we combine HMMs with longitudinal survey data to capture a latent, dynamic, multifaceted relationship state, as a function of four theoretically grounded, nonredundant, and underlying relational state variables from the most studied relational constructs in RM literature: commitment, trust, norms, and dependence (Frazier 1983; Heide and John 1992; Kumar, Scheer, and Steenkamp 1995; Morgan and Hunt 1994). We also model state migration using identified antecedents of relationship development that are under managerial control (Palmatier et al. 2006). Finally, to describe state performance, we use actual, account-level firm performance variables (i.e., sales revenue, account profitability, and sales growth). Our data set contains longitudinal survey and relationship performance data from 552 B2B relationships maintained by a *Fortune* 500 selling firm across a broad set of product categories.

This research contributes to RM literature in four main ways. First, our framework provides a holistic approach to the management of a portfolio of customers using theory-rich, multidimensional state variables that capture nonredundant information about relationship quality, rather than reducing complex buyer–seller exchange to a single construct, as much of extant research has done. Our theoretically based choice of four fundamental relationship constructs capture the subtle, but important, differences between customers who may appear similar if compared only by transactional metrics or by a single construct. Accordingly, our approach to relationship assessment has important implications for RM across diverse customers.

Second, our framework emphasizes the importance of tailoring RM strategies to the specific relationship state of the customer, made possible by our more holistic approach to relationship assessment. This contrasts with the vast majority of extant literature that has simply focused on increasing the *level* of the strategy indiscriminately across all customers, with the apparent assumption that strategies’ relative effectiveness is the same across states (e.g., Palmatier et al. 2006), which can lead to potential inefficiencies in relationship management. We empirically demonstrate that the most effective strategies must match the relationship state, and removing certain RM efforts at the wrong time can quickly undo prior relational developments.

Third, our research provides unique insights into the decline and recovery of relationships, which has received limited attention in marketing research to date. As Jap and Anderson (2007, p. 272) note, “Decline is a separate phenomenon, unique in its own right, and deserves more systematic research.” We show that decline is not a singular process but rather consists of two different mechanisms, each with corresponding consequences: Neglect is passive inattention, such that a seller that withholds relationship-sustaining resources is more likely to move the customer relationship from a more developed state to a neutral transactional state. Conversely, betrayal actively undermines the customer relationship, such that sellers who act in ways that lead to conflict or injustice are more likely to drive the relationship into a damaged state that persists only because of a high level of customer dependence. Although a relationship in a damaged state is more likely to remain damaged than to

improve in the next period, it might not always lead to dissolution, and it can be recovered through timely compromise—a result that contrasts with extant literature (Jap and Anderson 2007; Luo and Kumar 2013).

Fourth, on the basis of our preceding state conceptualizations, we develop and empirically test a framework that is parsimoniously described by three positive (exploration, endowment, and recovery) and two negative (neglect and betrayal) migration mechanisms. Each migration mechanism reflects unique patterns of relational variables (trust, commitment, norms, and dependence) that capture the development or decline of a relationship. From this framework, we provide managerially relevant insights into the effectiveness of state-specific relationship migration strategies, using an elasticity analysis. Accordingly, we empirically demonstrate that the common blanket application of RM strategies without regard to a customer’s relationship state is inefficient. Therefore, our research framework and results indicate there is no single most effective RM strategy. Firms must realize that greater RM efforts on all fronts do not always lead to better results and instead can constitute an inefficient use of resources.

## Understanding Customer Relationship States

We first review specific relationship state variables, defined as relational constructs that determine each state, before summarizing literature on relationship state conceptualizations (states), that is, the blend of state variables that individually capture different aspects of a relationship and together capture the multifaceted richness of buyer–seller relationships. Drawing on these two main concepts, we employ HMMs to infer relationship states, customer migrations across states, and the most effective RM strategies for inducing migrations. We label strategies that seek to promote or suppress state migrations, as a means to enhance relationship performance, as “dynamic relationship marketing.”

### Relationship State Variables

Different frameworks cite various state variables for determining a relationship’s state. Trust, commitment, dependence, and relational norms are the four state variables studied most frequently in RM. They provide nonredundant information and capture different facets of a relationship’s richness (Palmatier, Dant, and Grewal 2007). For example, a relationship state depends on both partners’ perspectives (partner and self), and whereas trust is more partner-focused, commitment is more self-focused (Garbarino and Johnson 1999). State variables provide information about individual partners (trust, commitment) and the bilateral structure of the exchange (dependence, relational norms). The four state variables also have different temporal characteristics: trust and dependence tend to change more quickly, whereas commitment and norms change more slowly (Jap and Ganesan 2000). Each state variable thus provides unique information about the relationship.

Perhaps the most studied variable, trust is defined as “confidence in an exchange partner’s reliability and integrity”

(Morgan and Hunt 1994, p. 23). This other-focused evaluation of a partner's integrity, reliability, and intentions can enhance performance by inducing risky but rewarding investments in the belief that the partner will not act opportunistically (Palmatier, Dant, and Grewal 2007). Trust implies that an exchange partner is consistent, honest, fair, responsible, helpful, and benevolent (Dwyer and LaGace 1986; Larzelere and Huston 1980; Morgan and Hunt 1994). Finally, trust helps a partner assess relationship quality and is a key predictor of performance (Fang et al. 2008).

Customer commitment is "an enduring desire to maintain a valued relationship" (Moorman, Zaltman, and Deshpandé 1992, p. 316). This state variable reflects self-focused attitudinal facets of an exchange, such as dedication, personal identification with the partner, and a focus on long-term benefits over short-term alternatives (Garbarino and Johnson 1999; Morgan and Hunt 1994). As a global evaluation of the relationship with a temporal facet, signaling expectations of continuity, customer commitment is key to the long-term success of a relationship (Palmatier et al. 2006).

Customer dependence reflects evaluations of partner-provided benefits for which there exist few alternatives (Hibbard, Kumar, and Stern 2001). Customers and sellers can create value by investing in relationship-specific assets, which increase dependence and exposure to opportunism (Wathne and Heide 2000). These assets are difficult to transfer without loss of productive value but often enhance performance. In addition, a high level of dependence can lock in a partner and prevent switching, even in the face of problems. Customer dependence is useful for assessing a relationship, in that it captures immediate evaluations of structural constraints with an exchange partner.

Finally, relational norms emphasize long-term concerns about a partner's prosperity, ensure equitable sharing of benefits and costs, reduce opportunism, and provide a normative governance structure because they "guide and regulate the standards of trade and conduct" (Gundlach, Achrol, and Mentzer 1995, p. 81; see also Heide and John 1990). Relational norms focus on and reflect the history of interactions between partners. Norms facilitate decisions and also are useful for evaluating the state of a relationship.

Trust, customer commitment, customer dependence, and relational norms provide a multifaceted view of a relationship, including partner versus self, individual versus bilateral structure, and short- versus long-term perspectives, which together define the relationship state. The four state variables all provide unique information about the relationship, have different temporal components, and do not always move in synchrony (Jap and Anderson 2007). We therefore believe that measuring a relationship's state on the basis of just one construct would provide an incomplete and potentially biased view of the overall health of that relationship.

### ***Relationship State Conceptualizations***

Relationship state conceptualizations (states) generally specify a set number of developmental stages to describe unique combinations of state variables, outcomes, and processes and thereby identify each state. Literature in this domain

related to customer life cycles is predominantly conceptual and exhibits little consensus about the appropriate number or nature of specific states, positing anywhere from two to six different options according to varying state variables. Our empirical research includes information only about current relationships in each sample year, so we do not observe the entire customer life cycle, from relationship initiation to dissolution. Nevertheless, we refer to life cycle literature to clarify possible state manifestations and how the four variables might vary in each state. As we summarize in Table 1, life cycle frameworks tend to consist of three fundamental states: an initial neutral or transactional state, a positive relational state (often divided into multiple substages), and a negative relational state.

In most frameworks, relationships start with low experience and norms (Jap and Anderson 2007), characterized by low to moderate interpersonal interactions and correspondingly low levels of relational state variables. Partners become aware of each other, often with minimal relational bonding, akin to what Anderson and Narus (1991) call "transactional exchanges." In some situations, this state can produce moderate financial performance because the parties engage in repeated, but possibly infrequent, transactions. Over time, some customers may be perfectly content to remain in this transactional mode without wanting to deepen the relationship further, whether because they are not relationship-oriented (Palmatier et al. 2008) or because the business at hand constitutes only a small portion of the client's entire business portfolio. Other customers seek opportunities to improve their relationships, with the goal of improving performance.

After this point of consensus, life cycle frameworks diverge considerably. Positive relationship states, which might be singular or contain three or more states (Heide 1994; Wilson 1995), can encourage the development of shared purposes, values, and expectations, as well as value-creating opportunities. This state(s) is characterized by increasing levels of trust and commitment; increasing interdependence as partners make nonrecoverable investments; and the establishment and augmentation of relational norms as the customer and seller explore, expand, and build their relationship (Dwyer, Schurr, and Oh 1987; Jap and Ganesan 2000). When relational variables and investments expand, the states feature improved relational and financial performance, beyond the initial transactional state. Along the positive state trajectory, there could be one or more developmental, or transitional, states before the relationship eventually stabilizes. In such states (e.g., "buildup" stages), the four relational variables should be increasing, even if at different rates and/or only for short periods (Palmatier et al. 2013; Ring and Van de Ven 1994), because both partners are working toward a common goal of improving the relationship and performance. In a communal state (i.e., mature, committed, partner, or relational state), relational variables and performance should reach their highest levels. We use the term "communal" because this state is mature, all aspects of the relationship are deeply and positively intertwined like a community, and performance is satisfactory and stable. Questions remain about how the transitional and communal states differ and whether the migration mechanisms moving to the

**TABLE 1**  
**Summary of Customer Relational States Research**

Reference	Methodology	Number of Relational States	Relational State Variables	Relational State Conceptualizations
<b>Conceptual</b> Dwyer, Schurr, and Oh (1987)	Conceptual	6	Trust, commitment, dependence, norms	Awareness–exploration–expansion–commitment–decline–dissolution
Rousseau et al. (1998)	Conceptual	3	Trust	Building–stability–dissolution
Ring and Van de Ven (1994)	Conceptual	4	Trust, dependence, norms	Negotiation–agreement–execution–assessment–dissolution
Heide (1994)	Conceptual/partial empirical test	3	Dependence, norms	Initiation–maintenance–termination
Wilson (1995)	Conceptual	5	Trust, commitment, social bonds, satisfaction, cooperation	Partner selection–defining purpose–setting relationship boundaries–creating relationship value–relationship maintenance
Johnson and Selnes (2004)	Conceptual, using simulation	3	Trust, commitment, satisfaction	Acquaintances–friends–partners
Anderson and Narus (1991)	Conceptual, using case studies	N.A.	Dependence, norms	Transactional vs. relational
<b>Empirical</b> Jap and Ganesan (2000)	Cross-sectional; age cohorts	4	Commitment, dependence, norms, satisfaction, bilateral investment, conflict	Exploration–buildup–maturity–decline
Hibbard, Kumar, and Stern (2001)	Cross-sectional; age as covariate	4	Trust, commitment, dependence, communication, shared values	Quartile 1 (age: 1–96 months)–Quartile 2 (age: 97–160 months)–Quartile 3 (age: 161–236 months)–Quartile 4 (age: 237+ months)
Netzer, Lattin, and Srinivasan (2008)	Longitudinal; hidden Markov model	3	Satisfaction, emotional connection, pride (for subset of sample)	Dormant–occasional–active
Jap and Anderson (2007)	Cross-sectional; age cohorts	4	Trust, dependence, norms (goal congruence) risk seeking	Exploration–buildup–maturity–decline
Palmatier et al. (2013)	Longitudinal; latent growth curve	N.A.	Commitment, commitment velocity	Continuous dynamic state
Luo and Kumar (2013)	Longitudinal; HMM	3	None	State 1 (lowest)–State 2–State 3 (highest)

Notes: N.A. = not applicable.

transitional state are different from those that lead to the communal state.

A final category is the negative relationship state, exhibiting low levels of trust, commitment, and norms, often due to some kind of relationship failure (Jap and Ganesan 2000; Samaha, Palmatier, and Dant 2011). A relationship with low state variables may terminate in subsequent periods if nothing holds the partners together and if a replacement can be found. However, because B2B relationships take a long time to establish (Gundlach, Achrol, and Mentzer 1995), and replacements of channel partners are difficult, a negative state could remain, such that the relationship is still alive and transactions still occur despite bad feelings in the interactions, leading the customer to look actively for an alternative channel. That is, when one partner is highly dependent on the other, the relationship might persist despite underlying problems (Frazier 1983). Depending on the circumstances, performance in a negative state exhibits diverging levels, often determined by the level of dependence (Scheer, Miao, and Palmatier 2015). However, such performance also might be a mirage; if the partners do not mend the relationship, dissolution will be on the horizon when partners eventually find alternatives.

## Dynamic Relationship Marketing: Drivers of Relationship State Migrations

Extant RM theory offers little insight into either the strategies that managers can use to influence customers' migration from different relationship states or how different migration strategies ultimately affect performance. In this sense, we seek to advance RM theory in two ways. First, drawing on our preceding state conceptualizations, we develop a theoretical framework to describe parsimoniously both the positive and negative state changes, using five migration mechanisms: exploration, endowment, neglect, betrayal, and recovery. Second, we hypothesize which RM strategies may be the most effective for influencing various migration mechanisms. On the basis of each strategy's effectiveness, we also can infer a strategy's performance impact.

### *HMM for Understanding Customer State Migrations*

Hidden Markov models are well suited for these tasks and have been used to infer latent relationship states from observed behaviors, such that customers can flexibly migrate between states (Luo and Kumar 2013; Montoya, Netzer, and Jedidi 2010; Zhang, Netzer, and Ansari 2014). Using data about alumni donation behaviors, Netzer, Lattin, and Srinivasan (2008) assign donors to latent states according to whether they express interest in donating; Ascarza and Hardie (2013) allow customers to migrate between states of likely or unlikely churn; Schweidel, Bradlow, and Fader (2011) consider latent states pertaining to customers' propensity for service usage with a multiservice provider; and Li, Sun, and Montgomery (2011) use purchase data about financial products to model states as consumers' latent financial sophistication. Some studies do not model migration explicitly (Ascarza and Hardie

2013; Netzer, Lattin, and Srinivasan 2008); others model it as driven by certain variables. For example, Montoya, Netzer, and Jedidi (2010) find that pharmaceutical reps' efforts drive physicians to migrate between latent states of high versus low awareness of a prescription drug. In one of the few empirical models of B2B relationships, Zhang, Netzer, and Ansari (2014) use pricing as a driver of state migration, such that when a buyer receives favorable pricing from a supplier, the buyer is more likely to migrate to a relaxed relationship state, whereas unfavorable pricing leads to a vigilant state.

The merits of employing HMMs to study dynamic RM are flexibility and parsimony. Beyond the flexibility to identify the number of states empirically, HMMs can show how "transient" or "sticky" different states are, and they allow for both gradual migrations in relationship states and transitions from one state to all others. These properties are well suited for B2B relationships, which often take time and effort to develop or decay but also can suddenly improve or deteriorate in extreme circumstances (e.g., after an injustice). In parsimonious terms, any current state depends only on the previous state and is independent of all previous migration paths. The relationship states that empirically emerge already contain all relevant information, regardless of the customers' past history.

In contrast with previous HMM studies that have sought to infer relationships on the basis of transactions, we infer latent, overall relationship states according to movements in the four theoretical state variables that measure different facets of the relationship. Our latent states thus have a strong theoretical basis, which constitutes an important contribution to RM theory. Likewise, we choose migration strategies that reflect widely studied variables in RM. We explicitly model migration paths as influenced by all possible RM strategies, which we chose according to two rationales. First, existing RM meta-analyses (Palmatier et al. 2006) identify commonly studied RM variables that are antecedents to the relationship state variables. Second, RM strategies should be both antecedents and marketing actions over which the seller has direct control. For example, relationship investments, communication, product mix, and conflict are appropriate RM variables because the seller can increase its investments in the relationship, communicate better or more frequently with the customer, improve product offerings, and actively adopt policies to avoid conflict. These actions then should affect the customer's perception of these variables and influence migration across relationship states.<sup>1</sup> Therefore, we investigate the following RM strategies (see the Web Appendix for details): conflict, communication, customer investment, seller investment, injustice, product mix, and compromise.

Our modeling approach includes all of these RM strategies in the HMM transition matrix; that is, the RM strategies are tested together across all migration paths and relationship

---

<sup>1</sup>This rationale of direct control is in contrast with the four state variables, over which the seller does not have direct control. For example, it would be difficult to increase perceptions of trust or commitment directly. Rather, such perceptions might be improved indirectly, as a result of firm-controlled actions, such as communication.

states. With this full specification, we can assess the relative effects of all RM strategies for each state and achieve our goal of identifying the most effective RM strategies for a given state, which in turn will provide managerial insights about how to adjust RM resources dynamically.

Because the unique mixture of state variables determines each customer's state, migrations are determined by changes in state variables. A relationship migration mechanism is the unique pattern of change in relational variables that leads to migration. In line with extant literature, we identify three positive (exploration, endowment, and recovery) and two negative (neglect and betrayal) relationship migration mechanisms, as shown in Figure 1. We describe each migration mechanism, reflecting the unique pattern of changes to state variables, and we hypothesize the most effective RM strategies for each mechanism (Table 2).

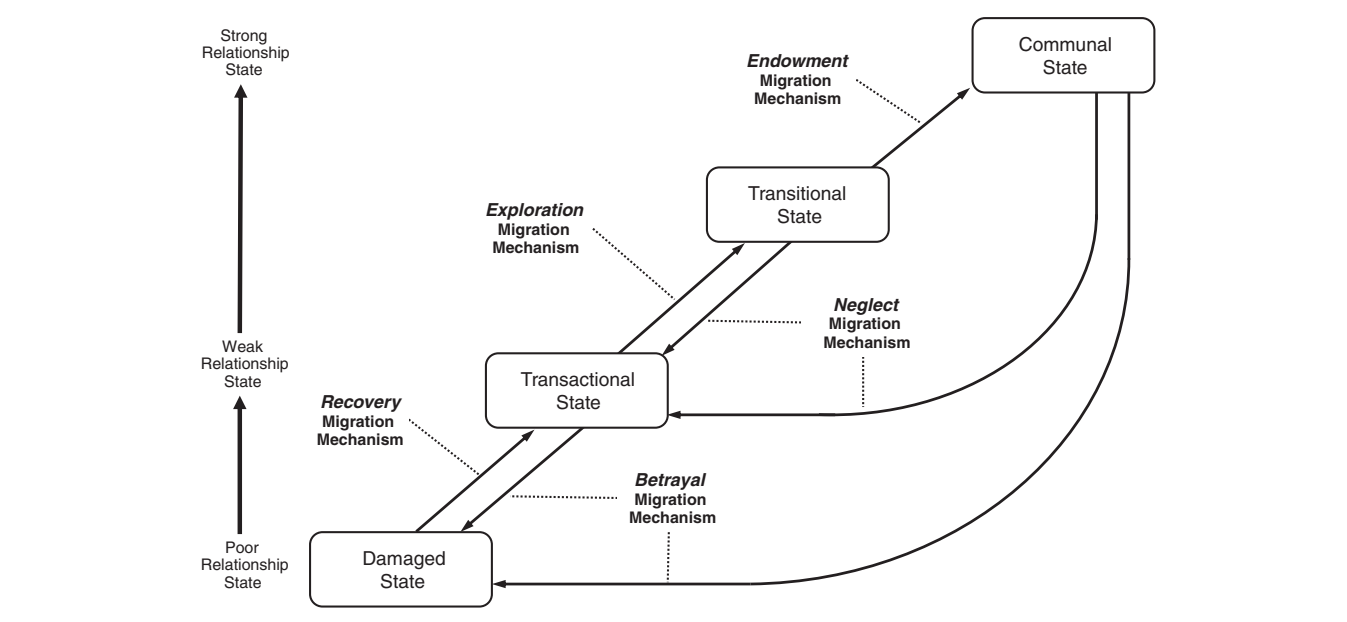
### Relationship-Building Migration Mechanisms

*Early development relationship states: exploration.* Buyer-seller interactions with low relational development, such as those that Dwyer, Schurr, and Oh (1987) describe as transactional, exhibit low to medium levels for the state variables. For relationships to migrate from this state in a positive manner, stronger relational bonds must develop through increased commitment and trust (Morgan and Hunt 1994). Repeated interactions that build relational governance (e.g., norms), through positive evaluations of reciprocal behaviors, also are crucial for continued relationship development (Cannon, Achrol, and Gundlach 2000; Heide and John 1992). Performance likely improves in step with stronger relational development, representing significant value creation through sales growth, for example. We refer to this pattern of change as an exploration relationship migration mechanism, because the customer explores the value creation potential of the

relationship and demonstrates a willingness to share rewards and costs as their relational bonds strengthen (Jap and Ganesan 2000). Identifying value-creating opportunities and building norms to share value are both key to exploration migration and the continuation of the relationship beyond arm's-length, one-time transactions.

Considering that exploration "refers to the *search and trial*" (Dwyer, Schurr, and Oh 1987, p. 16; italics added) portion of relational exchanges, with the main goals of "uncertainty reduction and an assessment of the potential value of continued interactions" (Jap and Ganesan 2000, p. 231), we believe two strategies from extant literature are most effective for facilitating the exploration mechanism: communication and product mix. Communication refers to the amount, frequency, and quality of information shared between partners (Mohr, Fisher, and Nevin 1996), such that it facilitates the search aspect of exploration. The flow of information from the seller reduces customer uncertainty as well as facilitates the search and identification of value-creating opportunities (Mohr, Fisher, and Nevin 1996). In addition, communication helps establish the goals and relational norms needed to govern the exchange and ensure an equitable division of value, which in turn increases confidence about investing for further value creation (Jap and Ganesan 2000). Although communication helps identify opportunities, a partner also must provide sufficient offerings and opportunity to fulfill its partner's needs. Product mix thus fulfills the trial aspect of exploration by capturing the seller's assortment and the variety of desirable products available to meet customer needs (Dwyer, Schurr, and Oh 1987). Because trials may include extended periods of testing and evaluation, an appropriate product mix provides an avenue through which norms may develop and build the relationship. Communication and product mix directly address the primary

**FIGURE 1**  
Overview of Relationship States and Migration Mechanisms



**TABLE 2**  
**Relationship Migration Mechanisms**

<b>Migration Mechanism</b>	<b>Definition</b>	<b>Pattern of Change in State Variables</b>	<b>Description of Effect on Exchange</b>	<b>Relevant State Transitions</b>	<b>Migration Strategies</b>	<b>References</b>
Exploration	Establishing the conditions through which both parties are willing and able to develop the relationship	<ul style="list-style-type: none"> <li>Stronger relational bonds through 9%–12% increases in trust, customer commitment, and customer dependence</li> <li>Significant increase in relational governance due to a positive evaluation of reciprocal behaviors as relational norms dramatically increase (29%)</li> </ul>	<ul style="list-style-type: none"> <li>Exchange performance rapidly grows</li> <li>Significant value creation through largest sales growth increase of any migration path</li> </ul>	<ul style="list-style-type: none"> <li>Transactional to transitional</li> </ul>	<ul style="list-style-type: none"> <li>Communication</li> <li>Product mix</li> </ul>	<ul style="list-style-type: none"> <li>Dwyer, Schurr, and Oh (1987)</li> <li>Jap and Ganesan (2000)</li> <li>Morgan and Hunt (1994)</li> <li>Mohr, Fisher, and Nevin (1996)</li> </ul>
Endowment	Bilateral investment intended to bring mutual value-creating opportunities to fruition	<ul style="list-style-type: none"> <li>Relational bonding between partners as trust, customer commitment, and relational norms increase additional 12%–16%</li> <li>Additional, large increase in dependence (26%) as both partners make nonrecoverable investments in the exchange</li> </ul>	<ul style="list-style-type: none"> <li>Cemented relational governance</li> <li>Investments in the exchange enhance performance to its highest level (e.g., sales revenue, cooperation highest in the communal state)</li> </ul>	<ul style="list-style-type: none"> <li>Transitional to communal</li> </ul>	<ul style="list-style-type: none"> <li>Seller investment</li> <li>Customer investment</li> <li>Seller × customer investment</li> </ul>	<ul style="list-style-type: none"> <li>De Wulf, Odekerken-Schröder, and Iacobucci (2001)</li> <li>Heide and John (1990)</li> <li>Palmatier, Dant, and Grewal (2007)</li> <li>Kozlenkova, Samaha, and Palmatier (2013)</li> </ul>
Neglect	Passive abuse indicating a lack of desire or resources to invest in the relationship	<ul style="list-style-type: none"> <li>Passive, downward state change results from erosion in state variables (10%–30% decay)</li> </ul>	<ul style="list-style-type: none"> <li>Always ends in the transactional state due to reduced contact and reduced social exchanges with the partner firm (but not necessarily reduced economic exchanges)</li> </ul>	<ul style="list-style-type: none"> <li>Communal to transactional</li> <li>Transitional to transactional</li> </ul>	<ul style="list-style-type: none"> <li>Low communication</li> <li>Low seller investment</li> <li>Low customer investment</li> </ul>	<ul style="list-style-type: none"> <li>Ping (1999)</li> <li>Joshi (2009)</li> <li>Koza and Dant (2007)</li> <li>Rusbult, Zembrodt, and Gunn (1982)</li> </ul>

**TABLE 2**  
Continued

Migration Mechanism	Definition	Pattern of Change in State Variables	Description of Effect on Exchange	Relevant State Transitions	Migration Strategies	References
Betrayal	Actively undermining fairness and damaging relational governance	<ul style="list-style-type: none"> <li>Immediate and dramatic state variable damage due to purposeful actions, typically accompanied by a strong emotional response</li> <li>Trust, customer commitment, and relational norms diminish by 36%–62%</li> <li>Relationship often saved from termination only by high dependence</li> </ul>	<ul style="list-style-type: none"> <li>Relational governance destroyed, with correspondingly low cooperation</li> <li>Exchange performance weak, with low sales growth often anchored in dependence</li> </ul>	<ul style="list-style-type: none"> <li>Communal to damaged</li> <li>Transactional to damaged</li> </ul>	<ul style="list-style-type: none"> <li>Conflict</li> <li>Injustice</li> <li>Conflict × injustice</li> </ul>	<ul style="list-style-type: none"> <li>Grégoire and Fisher (2008)</li> <li>Hibbard, Kumar, and Stern (2001)</li> <li>Samaha, Palmatier, and Dant (2011)</li> </ul>
Recovery	Repairing of norms, rebuilding trust, and moving relationship out of damaged state	<ul style="list-style-type: none"> <li>Entails substantial improvement in state variables, with trust, customer commitment, and relational norms typically needing greater than 50% improvement</li> <li>Must overcome relatively sticky nature of damaged relationship</li> </ul>	<ul style="list-style-type: none"> <li>Conflict and injustice resolved to repair relational governance and improve cooperation</li> <li>Exchange performance improves from negative (–3%) sales growth to moderate levels (5%)</li> </ul>	<ul style="list-style-type: none"> <li>Damaged to transactional</li> </ul>	<ul style="list-style-type: none"> <li>Communication</li> <li>Compromise</li> <li>Communication × compromise</li> </ul>	<ul style="list-style-type: none"> <li>Ganesan (1993)</li> <li>Dant and Schul (1992)</li> </ul>



roles of the exploration mechanism (search and trial), so we expect each of them to increase the likelihood that a relationship migrates from a less developed to a more developed relational state; we further expect them to be the most effective strategies for positively influencing the probability that a relationship migrates out of a neutral relationship state to a more developed one, due to their fundamental role in exploration. Both communication and product mix are relatively low-risk, high-reward strategies compared with relationship-specific investments, which can be costly and ineffective when deployed without due diligence to identify needs or value-creating opportunities (Brown, Dev, and Lee 2000).

H<sub>1</sub>: Among all RM actions, (a) product mix and (b) communication have the greatest effects on increasing the probability of migrating from a transactional to a transitional state.

*Advanced development relationship states: endowment.* Transitional relationships working toward the goal of a mature state must continue to develop trust, commitment, and relational norms to persist in strengthening relational bonds. In contrast with exploration, relational norms are already present at sufficient levels to promote buyer–seller governance in semiadvanced relationship states of this type (Dwyer, Schurr, and Oh 1987; Heide and John 1992). The crucial state variable to migrate to the most developed relationship is dependence, which can lock in a partner and prevent switching. It arises when the seller can offer, or endow, customer benefits that would be difficult to procure from other sources (Hibbard, Kumar, and Stern 2001). This endowment migration mechanism induces stronger relationships, with a great increase in dependence (Dwyer, Schurr, and Oh 1987; Jap and Ganesan 2000).

Given that relationship endowment (i.e., expansion or exploitation) refers to the “continual *increase in benefits* obtained by exchange partners and to their *increasing interdependence*” (Dwyer, Schurr, and Oh 1987, p. 18; italics added), we believe two strategies from extant literature are most effective for facilitating the endowment mechanism: seller and customer relationship investment. Prior research has indicated the key role of relationship investments, or “time, effort, spending, and resources focused on building a stronger relationship” (Palmatier et al. 2006, p. 138). These investments leverage partners’ value-creating capabilities by providing the resources necessary to exploit opportunities identified during the exploration mechanism (De Wulf, Odekerken-Schröder, and Iacobucci 2001) and thus increase exchange performance and benefits accrued from the relationship. Although a seller can invest resources to induce a more effective product mix through traditional means, such as accurate customer segmentation, targeting, and positioning to inform the development of its product line, these resources do not necessarily improve the customer relationship (Kahn 1998). Relationship investments (e.g., transaction-specific or idiosyncratic investments) are also the most effective strategies for increasing the dependence of an exchange partner because the difficulty of redeploying resources to other exchanges mitigates concerns of opportunism and signals

ongoing support for further investments (Heide and John 1990; Scheer, Miao, and Palmatier 2015). Considering that our context deals with a single, relatively powerful seller and many relatively weaker customers, we expect seller investments to have a greater impact than customer investments in inducing positive migration because the “[customer] perceives such investments as a credible pledge” to the relationship (Jap and Ganesan 2000, p. 230). This perception results in greater relationship strength, in that the customer knows that the seller will sustain economic consequences if the relationship ends (Anderson and Weitz 1992). Moreover, we expect a positive interaction between seller and customer investments. Reciprocal action theory suggests that when both parties provide resources, the opportunity to create synergistic value and self-reinforcing interdependence increases (Gouldner 1960; Kozlenkova, Samaha, and Palmatier 2013). Therefore, seller investments, and then customer investments, should have the greatest impact in terms of enhancing the endowment mechanism by providing the necessary resources to exploit opportunities and build a protective shield of interdependence. The result of these actions is a relationship that is communal in nature.

H<sub>2</sub>: Among all RM actions, (a) seller investments and (b) customer investments have the greatest effects on increasing the probability of migrating from a transitional to a communal state.

H<sub>3</sub>: The interaction of customer investments and seller investments positively affects the probability of migrating from a transitional to a communal state.

### **Relationship-Damaging Migration Mechanisms**

*Passive damage: neglect.* Highly developed relationships can also weaken, rather than continue to strengthen or remain in the same state. A negative but passive migration mechanism that describes state change is neglect, which captures a pattern of decay that is due to inattention rather than proactive negative activities. This change results from erosion in the state variables due to a failure to maintain the relationship. Often the relationship does not end, because neglect results in “reduced social exchanges with the partner firm (but not necessarily reduced economic exchanges with them)” (Ping 1999, p. 221). Marketing research on relationship decay and passive neglect is relatively limited, but social psychology literature has identified a lack of communication between partners as particularly detrimental (Rusbult, Zembrodt, and Gunn 1982). Lower levels of communication reduce trust, commitment, and norms but typically do not affect dependence, which is a structural constraint (Heide and John 1990). The reduction in ongoing communication thus results in neglect, which should increase the likelihood of a relationship returning to a transactional state.

Similarly, a seller reducing its relationship investments removes the resources required for value creation and signals a lack of relational motivation (Rindfleisch and Heide 1997), which suppresses trust, commitment, and relational norms in the customer, consistent with the neglect mechanism (Palmatier et al. 2008). Rusbult, Zembrodt, and Gunn (1982, p. 1239) argue that failing to continue to invest resources is “promotive of relatively destructive behaviors such as ignoring the partner.” Thus, reduced communication

or reduced customer and seller investments represent “passive strategies” for triggering the neglect migration mechanism, which increases the likelihood that a relationship will shift from a more developed relational state to a neutral state, in that it removes the factors that helped initially develop the relationship. Because of the passive nature of this decay, it is less emotional or purposeful as the exchange partners grow apart (Ping 1999), and the relationship likely drifts into a neutral or transactional state, rather than a more negative resentful or damaged state.

H<sub>4</sub>: Among all RM actions, reductions in (a) communication, (b) seller investments, and (c) customer investments have the greatest effects on increasing the probability of migrating from a higher relationship state to a neutral relationship state.

*Active damage: betrayal.* In addition to passive neglect, purposeful actions (or inadvertent actions perceived as purposeful by the customer) can significantly and immediately reduce relational state variables (Hibbard, Kumar, and Stern 2001). When sellers actively undermine the customer relationship, it implies betrayal, which involves an immediate, dramatic drop in the state variables due to purposeful actions, typically accompanied by strong emotional responses (Grégoire and Fisher 2008). Relationships with very low levels of trust, commitment, and norms may persist, however, because the continued exchange is held together by medium to high levels of dependence. Only dependent relationships usually survive betrayal, because they lack alternatives, despite the potential for anger and desire to punish the betrayer (Eyuboglu and Buja 2007). This strong emotional aspect and resultant drop in state variables distinguishes the consequences of betrayal from those of neglect.

For the betrayal mechanism to occur, there must be actions that sufficiently undermine the factors (e.g., state variables) that facilitate relationship performance and result in strong negative customer emotions. For this strong negative emotional reaction from the customer to arise, there must be sufficient cause for offense, attributable to the seller’s actions (Grégoire and Fisher 2008; Kaufmann and Stern 1988).

Conflict and injustice represent two migration strategies that are most likely to invoke a betrayal migration mechanism (Kaufmann and Stern 1988; Samaha, Palmatier, and Dant 2011). Unresolved conflict is an “interactive process manifested in incompatibility, disagreement, or dissonance” (Rahim 2002, p. 207). It can have detrimental impacts on relationship health, in that “the mere presence of relationship conflict demonstrates that parties do not share mutual understanding and appreciation, and will thus undermine trust” (Langfred 2007, p. 887). Incidence of conflict leads customers to have less confidence in the long-term orientation of the seller or less willingness to invest in building or maintaining a relationship, which in turn undermines commitment (Anderson and Weitz 1992).

Injustice is the customer’s perception of the degree of inequality in the procedures and processes of the seller. We focus on procedural injustice rather than distributive injustice, which is more directly under control of the seller and thus more attributable to seller behaviors (Kumar, Scheer, and Steenkamp 1995). For example, although just processes

and procedures help generate equitable outcomes, these outcomes may be obtained even if the seller’s procedures are not equitable. Conversely, outcomes may be comparatively inequitable despite just supplier procedures (Kumar, Scheer, and Steenkamp 1995). Injustice is not easily dismissible by the customer because unjust seller procedures provide the customer with negative information about the motives of the seller, which in turn produces emotionally powerful, negative attributions directly to the seller. These negative attributions produce a customer that is more likely to react punitively, making injustice especially damaging in a relationship setting (Kumar, Scheer, and Steenkamp 1995; Samaha, Palmatier, and Dant 2011). We also expect an interaction between conflict and injustice that can accelerate the migration of a relationship to the damaged state, because the presence of both conflict and injustice is particularly toxic to relational exchange (Campbell 1999; Samaha, Palmatier, and Dant 2011). Thus, both conflict and injustice represent key triggers of the betrayal mechanism, which increases the likelihood that a relationship will shift from a well-developed relational state to a negative or damaged state because it removes factors that underpin the exchange relationship and provoke significant negative emotional responses attributable to the seller.

H<sub>5</sub>: Among all RM actions, (a) injustice and (b) conflict have the greatest effects on increasing the probability of migrating from a higher state relationship state to a negative, damaged relationship state.

H<sub>6</sub>: The interaction of conflict and injustice positively affects the probability of migrating from a higher relationship state to a negative, damaged relationship state.

*Damaged relationship states: recovery.* The last migration mechanism is recovery, which describes the pattern of change in the state variables by which an exchange migrates from a negative/damaged state to a neutral/transactional state. It necessitates a substantial improvement in commitment, trust, and norms; the only state variable preventing complete relationship dissolution is likely high levels of dependence. Migration strategies to promote the recovery mechanism must work on the two principal characteristics of the damaged state. One is that the strategies must help rebuild the damaged relational state variables. The other is that the seller must resolve the conflict and injustice that drove the initial migration to the negative state.

As a result, we expect two strategies to be the most effective in facilitating the recovery mechanism: communication and compromise. Just as communication helps identify value-creating opportunities to promote relationship growth, it also is critical to relationship recovery as a means to identify and address the root causes of conflict and inequity, as well as to help mend relationship state variables (Ganesan 1993; Palmatier et al. 2006). However, communication alone may not be sufficient for recovery; after the problem is identified, partners must act on this information through compromise, or “the resolution of conflicts by developing a middle ground on a set of issues based on the initial positions of both parties” (Ganesan 1993, p. 186). Through compromise, partners directly address the conflict and inequalities that damaged the relationship by creating a more equitable exchange context. If

the seller is able to employ communication to facilitate identification of the problem while also making concessions to address relationship inequity, we expect a positive interaction these strategies. Thus, communication and compromise individually and synergistically represent migration strategies for promulgating the recovery mechanism.

H<sub>7</sub>: Among all RM actions, (a) communication and (b) compromise have the greatest effects on the probability of migrating from a negative/damaged state to a neutral/transactional state.

H<sub>8</sub>: The interaction of communication and compromise positively affects the probability of migrating from a negative/damaged state to a neutral/transactional state.

## Methodology

### Sample and Measurement

A large *Fortune* 500 firm participated in this research and granted us access to its business customers (channel members) over a six-year period. The firm sells hundreds of products across several dozen categories (e.g., housewares, clothing, books, tools, automotive products, consumer electronics, sports equipment, home appliances) and offers both branded and private-label items. Its approximately 1,600 business customers account for an average of \$600,000 in sales annually for the focal firm, and our study period revealed only 2% turnover among these customers, reflecting the longevity, stability, and switching costs inherent to B2B relationships (Jap and Ganesan 2000). This broad category sample should generalize effectively to B2B channel relationships, more so than a sample based in fewer product categories.

The data were collected through six consecutive annual surveys administered to the owner or senior manager of each channel member firm to ensure an accurate representation of the seller–customer relationship. These responses were then matched with the focal firm’s sales records for each channel member. The constructs included in each survey remained the same and were measured with identical items each year. In any particular year, an average of 57% of the channel members responded to the survey with usable responses. We thus defined our final sample as the 552 channel members that responded with usable questionnaires in at least four of the six years, so that we could effectively capture relationship dynamics.<sup>2</sup>

To test for nonresponse bias, we compared early and late responses for all waves of the study; these results suggested no differences ( $p > .05$ ). Multivariate analyses of variance of the study constructs and sales numbers indicated that responses by channel members that returned at least four of the six waves did not differ significantly from those of channel members that returned three or fewer waves ( $p > .05$ ). Comparable tests of demographic variables (age of relationship

---

<sup>2</sup>We also ran the full model on customers with five or more responses and customers with three or more responses. The substantive results remained the same, with larger parameter errors in the latter sample, such that we risked overfitting the data. Therefore, our chosen sample represents a middle ground between generalizability and reliability.

at time  $t$ ) in our final sample against those of firms with fewer responses or nonresponders also suggested no significant differences across groups.

The survey questions (see the Web Appendix) were the same in every data collection wave and were based on established and psychometrically tested multi-item scales from extant literature. Trust, customer commitment, customer dependence, relational norms, and profit assessments used five-point Likert scales (where 1 = “strongly disagree” and 5 = “strongly agree”). The firm provided objective financial measures of sales revenue and growth for each customer. For each year, we tested confirmatory measurement models by including all latent constructs in one model. We restricted each item’s loading to its corresponding construct and correlated each construct with all others in the model. Individual confirmatory factor analyses for each year yielded acceptable fit indices:  $\chi^2(836) = 1164.48-1669.39, p < .001$ ; comparative fit indices = .90–.95; Tucker–Lewis indices = .90–.94; root mean square errors of approximation = .04–.05; and standardized root mean square residuals = .04–.07.

To assess discriminant validity, we first confirmed that the square root of the average variance extracted exceeded its shared variances (intercorrelations) with all other constructs (Fornell and Larcker 1981) (see Table 3). Second, we executed an exhaustive pairwise comparison of constructs in a series of two-factor confirmatory measurement models. We ran each model first with the correlation between the two constructs constrained to unity, and then with a free estimation of the correlations. Across all construct comparisons, the chi-square difference tests supported discriminant validity ( $p < .01$ ). Furthermore, all scales also exhibited acceptable Cronbach’s alpha values from .73 to .95, in support of their internal reliability.

Although these data are censored, because the channel relationships existed both prior to and after the study period, we do not perceive censoring as a problem, for two reasons. First, we used the HMM framework to examine movement between the states of any given relationship, rather than tracking the entirety of the relationship life cycle. Thus, we model a sample of relationship state changes that tend to be generally infrequent in B2B relationships. Second, HMMs can use interval-censored data without issue (Luo and Kumar 2013), because the Markov chain depends only on the previous state, not the entire history of the relationship. Capturing six years of longitudinal survey data on relationship constructs is a rare and major undertaking in RM research, but it still might not represent the full life cycle, from the birth to the death of the relationship, and not all firms exhibit the same level of movement within this six-year window.

### Modeling Approach

Using the multivariate HMM, we empirically infer latent relationship states from the time-varying levels of each customer’s survey responses about the four state variables. The vector of state variables for customer  $i$  at time  $j$  is  $\mathbf{y}_{ij} = (t_{ij}, c_{ij}, d_{ij}, n_{ij})$ , where  $t_{ij}$ ,  $c_{ij}$ ,  $d_{ij}$ , and  $n_{ij}$  are the averages of the trust, commitment, dependence, and relational norm items, respectively. The latent state at time  $j$  for customer  $i$ ,



$\{\mathbf{Y}_{i1} = \mathbf{y}_{i1}, \dots, \mathbf{Y}_{ij} = \mathbf{y}_{ij}\}$ , has four components: (1) the initial latent state probabilities  $\boldsymbol{\pi}_i$ , which denote the customer's initial state; (2) a matrix of transition probabilities among states that explains how the customer moves from one period to the next, as well as the effects of various migration strategies on transition; (3) a multivariate likelihood of interrelated state variables, conditional on the relationship state  $L_{ij|s} = f_{is}(t_{ij}, c_{ij}, d_{ij}, n_{ij})$ ; and (4) the customer's latent state probability in each time period. We present the four-variate model as an intercept-only model. The coefficients for intercepts represent the average proclivity of each state variable, that is, the state variables' average levels. We do not place RM strategies in the utility model because we believe RM actions would result in gradual and long-lasting changes to the customer–firm relationship and thus should only influence state transitions.

*Initial state distribution.* Let  $s$  denote a latent relationship state ( $s = 1, 2, \dots, S$ ) and  $\pi_{is}$  be the probability that customer  $i$  is in state  $s$  in the first period of our data set, where  $\sum_{s=1}^S \pi_{is} = 1$ . We use  $S - 1$  logit-transformed parameters to represent the vector of initial state distribution.

*Markov chain transition matrix.* The HMM transition matrix denotes the probability a customer migrates from one state to each other, over periods, modeled as a Markov process:

		State at $t$					
State at $t - 1$		1	2	3	...	$S - 1$	$S$
$\boldsymbol{\Omega}_{i,j-1 \rightarrow j} =$	1	$\omega_{ij11}$	$\omega_{ij12}$	$\omega_{ij13}$	...	$\omega_{ij1S-1}$	$\omega_{ij1S}$
	2	$\omega_{ij21}$	$\omega_{ij22}$	$\omega_{ij23}$	...	$\omega_{ij2S-1}$	$\omega_{ij2S}$
	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
	$S$	$\omega_{ijS1}$	$\omega_{ijS2}$	$\omega_{ijS3}$	...	$\omega_{ijSS-1}$	$\omega_{ijSS}$

where  $\omega_{ijss'} = P(S_{ij} = s' | S_{ij-1} = s)$  is the conditional probability that customer  $i$  moves from state  $s$  at time  $j - 1$  to state  $s'$  at time  $j$ , and  $\forall s, s', \sum_s \omega_{ijss'} = 1$ . These transition probabilities might be influenced by several factors (i.e., migration strategies) at time  $j - 1$ . We define each transition probability as a function of migration strategies, using a logit specification to ensure  $0 \leq \omega_{ijss'} \leq 1$ . That is,

$$(1) \quad \omega_{ijss'} = \frac{e^{\mathbf{x}_{ij-1} \cdot \boldsymbol{\gamma}_s}}{1 + \sum_{s=1}^{S-1} e^{\mathbf{x}_{ij-1} \cdot \boldsymbol{\gamma}_s}},$$

where  $\mathbf{x}_{ij-1}$  is a vector of migration strategies affecting the transition between states and  $\boldsymbol{\gamma}_s$  is a state-specific vector of response parameters that measure the impact of each migration strategy on the transition probability  $\omega_{ijss'}$ . In our transition matrix specification, we include *all* possible RM strategies and hypothesized interactions so that we can compare the relative effects between all RM strategies for each migration path and identify the most effective strategy for each.

*HMM likelihood function.* Conditional on being in state  $s$  at time  $j$ , a customer responds to the levels of trust, commitment, dependence, and relational norms. These four responses are unconditionally interrelated. If customer  $i$  at time  $j$  is in a latent state  $S_{ij} = s$ , we can factor the conditional discrete–continuous joint likelihood using multivariate

normal distributions to model the joint distributions on all four variables, as follows:

$$(2) \quad L_{ij|s} = f_{is}(t_{ij}, c_{ij}, d_{ij}, n_{ij}),$$

where  $t_{ij}$ ,  $c_{ij}$ ,  $d_{ij}$ , and  $n_{ij}$  are trust, commitment, dependence, and relational norms, respectively. Considering the Markovian structure of the model, the likelihood of observing a set of joint customer responses at time  $J$  depends on all responses prior to that event. The likelihood of customer's responses over  $J$  periods ( $\mathbf{Y}_{i1}, \mathbf{Y}_{i2}, \dots, \mathbf{Y}_{iJ}$ ) is

$$(3) \quad L_{iJ} = P(\mathbf{Y}_{i1} = \mathbf{y}_{i1}, \dots, \mathbf{Y}_{iJ} = \mathbf{y}_{iJ}) = \boldsymbol{\pi}_i \mathbf{M}_{i1} \boldsymbol{\Omega}_{i,1 \rightarrow 2} \mathbf{M}_{i2} \dots \boldsymbol{\Omega}_{i,J-1 \rightarrow J} \mathbf{M}_{iJ} \mathbf{1}',$$

where  $\boldsymbol{\pi}_i$  is the initial state distribution,  $\boldsymbol{\Omega}$  is the transition matrix,  $\mathbf{M}$  is an  $S \times S$  diagonal matrix with the elements  $L_{ij|s}$  from Equation 1 on the diagonal, and  $\mathbf{1}'$  is an  $S \times 1$  vector of ones.

To ensure identification of the states, we restrict customers' responses to trust to be nondecreasing in the relationship states. Let  $\beta_{b01i}$  be customer  $i$ 's mean-level response to trust in state 1, with the lowest trust, such that we set  $\beta_{t0si} = \beta_{t01i} + \sum_{s=2}^S \exp(\beta_{t0s'i})$ ;  $s = 2, \dots, S$ . To avoid underflow, we scale the likelihood function in Equation 2 (MacDonald and Zucchini 1997).

*Recovering state membership distribution.* We use a filtering approach (Hamilton 1989) to determine the probability that customer  $i$  is in state  $s$  at time  $j$ , conditional on the customer's history:

$$(4) \quad P(S_{ij} = s | \mathbf{Y}_{i1}, \mathbf{Y}_{i2}, \dots, \mathbf{Y}_{ij}) = \boldsymbol{\pi}_i \mathbf{M}_{i1} \boldsymbol{\Omega}_{i,1 \rightarrow 2} \mathbf{M}_{i2} \dots \boldsymbol{\Omega}_{i,j-1 \rightarrow j} \cdot s L_{ij|s} / L_{ij},$$

where  $\boldsymbol{\Omega}_{i,j-1 \rightarrow j} \cdot s$  is the  $s$ th column of the transition matrix  $\boldsymbol{\Omega}_{i,j-1 \rightarrow j}$ , and  $L_{ij}$  is the likelihood of the sequence of joint state variables up to time  $j$  from Equation 2.

In our HMM, latent relationship states are determined by each customer's time-varying levels of survey responses to the four state variables. It simultaneously identifies the number of latent states, allows customers to migrate freely across different states, and assesses the effectiveness of each RM strategy on migration path. In the following section, we accordingly discuss the number of states and their characteristics, as empirically identified by the model, followed by the identified migration paths and the most effective RM strategies for each path.

## Results

### Number of States and Model Comparisons

We have no a priori knowledge about the exact number of relationship states, so we estimate two-state to five-state models, with the full set of RM strategies, and select the one that offers the best fit, according to the deviance information criterion (DIC), which accounts for model complexity. The results show that the four-state HMM fits the data best. As we report in Table 4, significantly different mixtures of state variables and outcomes arise for the four relationship states. In addition, in the migration path probability matrix, the diagonal represents the mean probability of remaining in the same state (i.e., stickiness),

and off-diagonal values indicate the probabilities that a customer in a given state will migrate to a different state.

To assess the extent of dynamics and heterogeneity, we performed multiple model comparisons and robustness checks, with the results summarized at the bottom of Table 4. If the relationship states are truly dynamic, we expect a better fit from HMMs than from static latent class segmentations. Thus, we compare the fit of our HMM against three-, four-, and five-state latent class segmentation models, for which the DICs were significantly worse than the comparable values for the fully specified HMMs. Thus, significant variance appears due to relationship dynamics within the same customer, instead of cross-sectional differences among customers. To assess whether the migrations are random or influenced by RM strategies, we test a set of HMMs but without variable specifications in the transition matrix; they provide worse fit. Therefore, the set of RM strategies can explain state migrations.

The customers in our data set come from various industries, with potentially different dynamics and product requirements, but we do not have data about the industry each customer represents. We thus need to assess unobserved heterogeneity. In theory, our data set should not suffer much from heterogeneity because (1) the survey questions about relational constructs are general attitude measures that should normalize across firms, and (2) incorporating the product mix construct in our model captures some heterogeneity in that certain industries should value the product mix more than others. To test the extent of unobserved heterogeneity more formally, we ran additional versions of a two-latent segment/four-state model, as well as a three-latent segment/four-state model. Thus, we imagine our samples containing two or three types of customers whose unobserved characteristics do not change over time. The fit results are worse than those of our chosen model. Therefore, the amount of time-invariant heterogeneity, after we account for these two factors, is not enough to overcome the additional model complexity. Furthermore, we checked alternative specification of the model using ordinal logistic regression and found the same substantive results but slightly worse fit. This battery of model comparisons and robustness checks suggests our model parsimoniously captures dynamics, identifies the number of states, and properly specifies migrations, influenced by RM strategies.

Furthermore, as additional controls, the transition matrix includes, for each customer, the total square footage of its store, as well as the percentage dedicated to the seller's business, along with the number of employees and the percentage of them dedicated to the seller's business. Together, these variables control for economic expansion/contraction and for competitive intensity, which might shift the customer's business focus and influence the seller's RM efforts, but we find no significant effects. In our approach, we estimate aggregate parameters instead of individual-level parameters; the variation in movements among customers and the richness in four state variables provide pooling of information among firms, which allows us to identify the four states. A Markov chain Monte Carlo simulation with six data points on four observed variables, wherein we "observe" the latent states, has a state recovery hit rate of 73.7%, which is sufficiently high to allow us to describe the relationship states in our empirical application.

We would need more than six data points to accurately estimate individual parameters.

### **Identifying Relationship States**

The transactional state is where most relationships begin ( $M_{\text{age}} = 3.9$  years), characterized by low to medium levels of trust ( $M = 3.61$ ), customer commitment ( $M = 3.66$ ), and customer dependence ( $M = 2.43$ ),<sup>3</sup> as well as relatively low relational norms ( $M = 2.38$ ). This mixture implies a neutral, undeveloped relationship, with little embedded relational governance. Relationships in the transactional state exhibit moderate levels of profit ( $M = 3.69$ ) and sales growth (5%) and represent the largest portion across the four states (54% of total sample). This state is unique because it exhibits the most heterogeneous state migrations. Relationships move to stronger relational states 41% of the time, move to weaker or damaged relational states 16% of the time, and remain in the same state 43% of the time. The transactional state also is evaluative, such that parties receive some value from their exchanges but also explore opportunities to create more value before making significant investments.

Following a positive migration trajectory, relationships move from the transactional state to a state that exhibits medium to high levels of trust ( $M = 4.02$ ), commitment ( $M = 4.16$ ), and relational norms ( $M = 3.37$ ) and low to medium customer dependence ( $M = 2.67$ ). Two characteristics define this state. First, all the state variables are higher than in the previous state, and the change in relational norms is more than three times greater than that in the other state variables, reflecting a substantial increase in relational governance. Second, it is the least sticky state; in each period, 75% of relationships migrate to another state (60% strengthening, 15% weakening). We thus refer to it as the transitional state; most relationships are in the process of shifting from a transactional to the most developed relational state and are unlikely to remain transitional for more than one period. Profits ( $M = 3.82$ ) and annual sales growth (23%) are higher than in the transactional state, indicating growth in the potential of the relationship.

The communal state exhibits the highest levels of trust ( $M = 4.73$ ), commitment ( $M = 4.74$ ), customer dependence ( $M = 3.58$ ), and relational norms ( $M = 4.02$ ). Strong relational development produces the highest levels of profit ( $M = 4.325$ ) and good sales growth (12%). In terms of migration, the communal state is the most sticky (61% remain each period), but if the relationship changes, it is more likely to move directly to the weakest relational state (21%), rather than migrating to a neutral status, such as the transactional state (15%). Thus, transgressions appear more damaging in the communal state.

Finally, the damaged state is marked by low levels of trust ( $M = 2.54$ ) and commitment ( $M = 2.67$ ) and very low

---

<sup>3</sup>We use the terms "low," "medium," and "high" relatively, to refer to the empirical range for each state variable, because customers have different perceptions and baselines for the different survey items. Thus, 3 would be a relatively high score for dependence but low to medium for trust. In Table 4, we use asterisks to indicate state variables that are statistically significantly different from their neighbors at the .05 level.

**TABLE 4**  
**Results: HMM of Relationship States**

<b>A: Relational States</b>						
	Measure	State Name				
		Transactional	Transitional	Communal	Damaged	
<b>Relational State Variables</b>						
Trust (mean)	1–5 scale	3.61*	4.02*	4.73*	2.54*	
Customer commitment (mean)	1–5 scale	3.66*	4.16*	4.74*	2.67*	
Customer dependence (mean)	1–5 scale	2.43	2.67	3.58*	3.16*	
Relational norms (mean)	1–5 scale	2.38*	3.37*	4.02*	1.51*	
<b>Performance Outcomes</b>						
Profit (mean)	1–5 scale	3.69	3.82	4.25	3.09	
Sales growth	Annual %	5%	23%	12%	–3%	
Sales revenue	\$1,000	549	609	812	629	
<b>Relationship State Descriptors</b>						
Percentage of sample across all years	%	54%	9%	24%	13%	
Relationship duration	Years	3.9	5.4	7.4	5.8	
<b>B: Migration Probabilities</b>						
Migrate From	Migrate To					
	Transactional State	Transitional State	Communal State	Damaged State		
Transactional state	42.9%	40.6%		15.6%		
Transitional state	10.9%	25.5%	59.8%	3.8%		
Communal state	15.4%		60.5%	20.9%		
Damaged state	39.6%			56.4%		
<b>C: Model Fit Comparisons</b>						
	Three-State	Four-State	Five-State	Two-Segment	Three-Segment	Ordinal Logit
<b>Latent Class—No Dynamics</b>						
Log-likelihood	–14,170.32	–12,662.33	–13,415.57			
DIC	28,883.74	25,809.96	27,345.31			
<b>Dynamic Model—No Specification in Transition</b>						
Log-likelihood	–11,585.83	–10,742.98	–11,109.10			
DIC	23,615.71	21,897.70	22,643.98			
<b>Dynamic Model—Full Specification in Transition</b>						
Log-likelihood	–10,461.23	–9,846.30	–10,731.86			
DIC	21,323.40	20,063.98	21,875.03			
<b>Four-State HMM with Segments</b>						
Log-likelihood				–9,872.38	–9,898.18	
DIC				20,419.40	20,659.64	
<b>Ordinal Logit Model</b>						
Log-likelihood						–9,994.40
DIC						20,237.22

\* $p < .05$ .

Notes: DIC = deviance information criterion.

levels of relational norms ( $M = 1.51$ ) but medium to high levels of customer dependence ( $M = 3.15$ ). The combination of low trust, commitment, and norms with higher dependence results in divergent relational and financial performance. Sales growth (–3%) is negative, yet these relationships appear relatively profitable ( $M = 3.09$ ), likely because of customer dependence. Exiting the damaged state is difficult; 56% of the relationships remain stuck

here, and if they recover, they move only to the relationally neutral transactional state. Exchanges in the damaged state feature not undeveloped but, rather, negative relationships. Given their relatively larger account size and probability of having arrived from the communal state, these relationships likely have declined substantially in their health. If not for high dependence, many of them would dissolve.

**TABLE 5**  
**Results: Effect of State-Specific Migration Strategies**

Migration Mechanism	Migration Probability	Effect of Migration Strategies on Migration Probabilities										
		Intercept	Communication	Product Mix	Seller Investment	Customer Investment	Bilateral Investment	Conflict Attribution	Injustice Attribution	Conflict Attribution	Compromise x Communication	
<b>Exploration</b> Transactional to transitional	41%	-7.90*	<b>.51*</b>	<b>.61*</b>	.30*	.45*	.23	-.23*	-.34*	-.32*	.03	.05
<b>Endowment</b> Transactional to communal	60%	-11.59*	.12	-.02	<b>.63*</b>	<b>.52*</b>	.43*	-.30*	-.34*	-.34*	.31*	.32*
<b>Neglect</b> Transactional to transactional	11%	9.25*	<b>-.54*</b>	-.38*	<b>-.64*</b>	<b>-.51*</b>	-.27*	.43*	.15	.22*	-.07	-.06
Communal to transactional	15%	7.45*	<b>-.40*</b>	-.13	-.34*	<b>-.55*</b>	-.25*	.37*	.24*	.33*	-.24	-.19
<b>Betrayal</b> Transactional to damaged	16%	.30*	-.11	-.11	-.13	.03	-.02	<b>.31*</b>	<b>.32*</b>	<b>.29*</b>	-.22	-.17
Transactional to damaged	4%	-2.32*	-.18*	-.03	-.18	.07	-.18*	<b>.39*</b>	<b>.50*</b>	<b>.39*</b>	-.02	-.02
Communal to damaged	21%	4.10*	-.50*	-.07	-.49*	.42*	-.26*	<b>.58*</b>	<b>.84*</b>	<b>.63*</b>	-.43*	-.34*
<b>Recovery</b> Damaged to transactional	40%	-7.12*	.21*	.07	.06	.19*	.05	-.17	-.20*	-.42*	<b>.55*</b>	<b>.41*</b>

\* $p < .01$ .

Notes: Italics indicate the most effective strategies for a given migration mechanism, as proposed by the hypotheses. Boldface indicates values that are significantly different from the rest of the estimates (at  $p < .05$ , according to t-tests) for a given migration mechanism.



### **Effectiveness of Relationship Migration Strategies: Dynamic Relationship Migration**

Table 5 presents the parameter estimates of all RM strategies across all migration paths. This comparison allows us to highlight the most effective strategy or strategies for each path; italic values in the table represent the strategies that we hypothesized would be most effective for a given migration, and boldface indicates strategies that differ statistically at the .05 level from the other strategies for a given migration path as determined by t-test. Conditional on being in a transactional state, both product mix ( $\beta = .61, p < .01$ ) and communication ( $\beta = .51, p < .01$ ) significantly increase the probability of moving a customer to the transitional state and are stronger motivators of this relationship change than all other strategies we tested, in support of  $H_{1a-b}$  and the underlying exploration migration mechanism. In support of the endowment mechanism, partners can increase the probability of advancing their relationship from a transitional to the communal state by making seller ( $\beta = .63, p < .01$ ) and customer ( $\beta = .52, p < .01$ ) investments, which are the most effective strategies for relationships in the transitional state, in support of  $H_{2a-b}$ . The positive interaction between customer and seller investments promotes the migration of partners to the communal state ( $\beta = .43, p < .01$ ), in support of  $H_3$ .

For the two relationship-damaging mechanisms, we find that reductions in communication ( $\beta = -.54, p < .01$ ), seller investment ( $\beta = -.64, p < .01$ ), and customer investment ( $\beta = -.51, p < .01$ ) have the greatest impacts on shifting a relationship from the transitional to the transactional state, in support of  $H_{4a-c}$  and the neglect mechanism. Similarly, reducing the levels of communication ( $\beta = -.44, p < .01$ ), seller investment ( $\beta = -.34, p < .01$ ), and seller investment ( $\beta = -.55, p < .01$ ) increases the probability of shifting a relationship from the communal to the transactional state. The effects of reducing communication or seller investment in the communal relationship are significant but are not statistically different from the effect of increasing conflict (.40, .34, and .37, respectively;  $p > .05$ ), yet reduction in customer investments has statistically stronger effects than the nonhypothesized strategies, in further support of  $H_{4a-c}$ . Reducing seller investment is more detrimental (vs. other types of RM reductions) to moderately developed (i.e., transitional) relationships, whereas reducing communication is more detrimental to more developed (i.e., communal) relationships.

Worse than neglect, the betrayal mechanism drives a relationship to the damaged state through conflict and injustice. As we predicted in  $H_{5a-b}$ , injustice ( $\beta = .50, p < .01$ ) and conflict ( $\beta = .39, p < .01$ ) increase the likelihood that a transitional relationship moves to the damaged state. Similarly, in support of  $H_{5a-b}$ , injustice ( $\beta = .84, p < .01$ ) and conflict ( $\beta = .58, p < .01$ ) have the greatest impacts on degrading communal relationships to the damaged state; being perceived as unjust is especially harmful. Each of these hypothesized migration strategies exhibits stronger effects than other, nonhypothesized strategies. The significant, positive interaction effect between conflict and injustice (conflict attribution) enhances the probabilities of migrating from the communal ( $\beta = .63, p < .01$ ), transitional ( $\beta = .39,$

$p < .01$ ), and transactional ( $\beta = .29, p < .01$ ) states to the damaged state, in support of  $H_6$ . Accordingly, the more developed the relationship, the more damaging conflict and injustice appear to be.

Finally, we evaluate the recovery migration mechanism, which moves customers from damaged to transactional states due to intentional transgressions. As we expected, the direct effect of compromise ( $\beta = .55, p < .01$ ) has the greatest impact on transitioning out of the damaged state, in support of  $H_{7a}$ . Communication ( $\beta = .21, p < .01$ ) has a significant direct impact on the likelihood of migrating to the transactional from the damaged state, but it is not statistically greater than that of customer investment (.21 vs. .19,  $p > .05$ ), in partial support of  $H_{7b}$ . Moreover, the interaction between communication and compromise is significant ( $\beta = .41, p < .01$ ), in support of  $H_8$ .

### **Relationship Migration Strategies' Elasticities**

To understand the performance consequences of applying state-specific migration strategies, we ran a series of hypothetical scenarios that featured one-standard-deviation changes to factors under the control of the selling firm, such as communication or seller investment, but in which the status quo was maintained for all other factors. By examining the resulting changes in the mean transition matrices, we calculated the elasticity of a migration strategy and derived associated managerial insights related to the relative effectiveness of a strategy across states and the performance implications of applying such a strategy. Table 6 presents the elasticity analysis results for each relationship migration mechanism. We present the results as elasticities; for a 1% shift in the migration strategy of interest, we identify the corresponding percentage change in the probability of moving from one relationship state to another.

*Exploration.* As we show in Table 6, the most effective strategy for migrating a customer in a neutral, transactional state to the higher, transitional state is communication (1.44%), followed by product mix (1.33%). For comparison purposes, we note that these two strategies are more effective for this migration mechanism than three other migration strategies: seller investment (.81%), customer investment (.97%), and compromise (.17%). Both strategies also have greater marginal returns in the exploration mechanism (i.e., relationships in the transitional state) than in the two other relationship-building migrations, the endowment (product mix = .11%, communication = .46%) and recovery (product mix = .15%, communication = .52%) mechanisms. Targeting customers in the transactional state by increasing communication or product mix by 10% would yield a \$1,040,483 or \$961,002 increase in revenue in the next period, respectively—roughly equivalent to adding almost two new accounts. Both strategies induce a slightly greater increase in the probability of moving from the transitional to the communal state, but they are less than 36% as effective when applied to other states in increasing the probability of migration, which underscores the benefit of communication and product mix strategies for undeveloped relationships.

**TABLE 6**  
**Results: Elasticities of State-Specific Migration Strategies**

A: Positive Migration Mechanisms						
Migration Mechanism	Calculation Method <sup>a</sup>	Migration Strategy Elasticity				
		Communication	Product Mix	Seller Investment	Customer Investment	Compromise
<b>Exploration</b>						
Transactional to transitional	Increase	1.44%	1.33%	.81%	.97%	.17%
<b>Endowment</b>						
Transitional to communal	Increase	.46%	.11%	1.20%	.90%	.43%
<b>Recovery</b>						
Damaged to transactional	Increase	.52%	.15%	.14%	.90%	1.13%

B: Negative Migration Mechanisms						
Migration Mechanism	Calculation Method <sup>a</sup>	Migration Strategy Elasticity				
		Communication	Seller Investment	Customer Investment	Conflict	Injustice
<b>Neglect</b>						
Transitional to transactional	Decrease	-2.77%	-4.72%	-3.36%		
Communal to transactional	Decrease	-.98%	-.71%	-2.31%		
<b>Betrayal</b>						
Transitional to damaged	Increase				1.31%	1.59%
Communal to damaged	Increase				.97%	1.43%

<sup>a</sup>The point elasticities were calculated by increasing or decreasing a single migration strategy (e.g., communication) by one standard deviation and examining the percentage change in migration probability from one relationship state to another.

*Endowment.* For relationships in the transitional state, the most effective strategy for moving customers to the communal state is seller investment (1.20%), which is substantially more effective than communication (.46%) or product mix (.11%). Presumably, the information and value created in earlier states already are known to both parties. Applying seller investments also provides the most marginal benefit for increasing the probability of migration compared with transactional (exploration: .81%) or damaged (recovery: .14%) relationships. A 10% increase in seller investment applied to relationships in the transitional state would yield a \$725,940 increase in revenue in the next period in our sample. If the customer also is willing to invest in the relationship (.90%), this strategy, though outside the focal firm's control, benefits both parties, as does a willingness to compromise (.43%). However, seller investment is the key strategy for emerging relationships because it provides resources for more successful value creation.

*Neglect.* Rather than increase the levels of each migration strategy, we can reduce the levels one at a time to understand the effect of neglect on more developed relationships. We find especially high elasticities, indicating the strongly detrimental effect of starving a customer relationship. For example, for relationships in the less stable transitional phase,

reductions in seller investment (-4.72%) and communication (-2.77%) are substantially more likely to lead a relationship back to the transitional state than are similar reductions in seller investment (-.71%) and communication (-.98%) when relationships are in the most developed, communal state. A 10% decrease in communication or seller investment for relationships in the communal state would yield \$408,206 and \$295,741 decreases in revenue in the next period.

*Betrayal.* To examine the other relationship-damaging mechanism, we increase the levels of conflict and injustice to determine their effect on driving more developed relationships toward the damaged relationship state. Again, relationships in the transitional state are less stable and more prone to damage. For example, a transitional relationship exhibits more sensitivity to increases in conflict (1.31% vs. .97%) and injustice (1.59% vs. 1.43%) than a communal relationship. Injustice is 21%–47% more caustic to the customer relationship than conflict. Accordingly, 10% increases in conflict and injustice applied to relationships in the communal state would yield \$491,813 and \$725,044 decreases in revenue in the next period, respectively.

*Recovery.* If a customer relationship deteriorates to a damaged state, it can be difficult, though not impossible, to

recover. However, a manager who attempts to salvage a poor relationship with greater communication (marginal return: .52%), product mixes (.15%), and seller investments (.14%) is making inefficient uses of the firm's resources; compromise (1.13%) offers better marginal returns. In our sample, the average account size in a transactional relationship is smaller than that of a damaged relationship, so a 10% increase in compromise applied to damaged relationships would actually yield a \$257,222 decrease in revenue in the next period.

## Discussion

Using an HMM with six years of survey data collected from 552 business relationships maintained by a *Fortune* 500 seller, we capture dynamic relationship state changes using theory-rich relational state variables (commitment, trust, norms, and dependence) and associate them with real, account-level firm performance variables (profitability and sales growth). This framework allows us to build on extant theory and managerial practice.

### Theoretical Implications

This study advances RM theory in three key ways. First, we identify and define three positive (exploration, endowment, recovery) and two negative (neglect, betrayal) relationship migration mechanisms that parsimoniously account for observed customer state changes. Each positive migration mechanism builds relational variables at different times and in different patterns and reflects the potential development and decline of a customer relationship. Relationships with lower levels of development demand increases to relational variables, such as trust and commitment. More developed relationships instead must build mutual dependence and relational governance through norms.

Second, we expand on two important areas of relationship management that have been largely neglected by extant literature: decline and recovery. We show that decline is not a singular process but can damage relationships through distinctly different mechanisms. Neglect is passive inattention, such that partners withhold relationship-sustaining resources and move the relationship to a transactional state. Betrayal actively undermines relational equity, driving the relationship into a damaged state due to direct negative attribution to the seller of unfavorable behaviors. Considering that damaged relationships likely persist due to higher levels of dependence (Jap and Anderson 2007), severing ties is not necessarily the best or only option; timely compromise can help sellers address relational issues to repair damaged relationships.

Third, our research framework and results indicate there is no single effective RM strategy; there are only effective, state-specific RM strategies. For example, improving communication and product mix is 79% and 93% less effective, respectively, when applied to more developed relationships rather than less developed, transactional relationships. The correct strategy must match the relationship state; removing marketing actions at the wrong time also can quickly undo prior relational development. A reduction in seller investment in the transitional state is 3.9 times as likely to result in a

negative migration to the transactional state as an identical increase is to produce a positive migration to the communal state (-4.72% vs. 1.20%). Whereas extant literature has sought to describe the relationship states, we advance RM theory with a detailed understanding of state migration mechanisms, as well as the most effective RM strategies and synergies for each migration.

### Managerial Implications

Whenever possible, managers should consider multiple facets of a customer relationship, because what may appear to be one type of relationship actually may be another, and the identification can have important implications for appropriate managerial action. For example, different patterns of all four state variables determine unique state conceptualizations. Although trust and commitment tend to move in unison, divergent levels of relational norms and dependence are important for state identification. Frameworks that fail to include one of these critical state variables thus may be unable to identify or distinguish a transactional state from a damaged state across a portfolio of customers (e.g., Palmatier et al. 2013). Relying purely on performance measures to infer relationship states, although convenient, could be misleading. For instance, damaged relationships appear larger in size (average account size of \$629,000) than either transactional (\$549,000) or transitional (\$609,000) relationships; yet account size is deceiving, and each of these states demands substantially different treatment in terms of migration strategy. Therefore, managers must realize that account performance and relationship state do not always align intuitively, and developing marketing actions without looking deeply into the underlying relationship can lead to inefficient resource allocations. A comforting finding is that even though a relationship in a damaged state is roughly 50% more likely to remain damaged than to improve, it does not necessarily lapse into dissolution and can be recovered through timely compromise—a result that contrasts with extant literature (Dwyer, Schurr, and Oh 1987; Luo and Kumar 2013). We make a case for investigating the dynamics and multiple facets of a customer's relationship, then applying appropriate, state-specific RM strategies to achieve the best returns.

In Table 7, we list rules of thumb that managers can use to identify the relationship states of their customers, deploy relevant RM migration strategies given the states, and predict the payoffs from these strategies. In the column labeled "Distinguishing Relationship State Characteristics," we describe each of the four relationship states in terms of state variable levels, the financial performance characteristics, the customer size in the portfolio, and the movement characteristic, such as where the relationship state originates from and where it is likely to migrate to. For instance, customers in transactional states are generally new customers, and they comprise the majority of the customer portfolio. Levels of trust, commitment, norms, and dependence are low in this state, with correspondingly low levels of sales and sales growth. Many of these relationships remain transaction-oriented. By comparing relative performance levels and relative magnitude of state variables (i.e., trust, commitment, norms, and dependence) across all customers through regularly fielded survey efforts,

**TABLE 7**  
**Managerial Insights into Dynamic Relationship Marketing Strategies**

Relationship State	Distinguishing Relationship State Characteristics	Dynamic Relationship Marketing Migration Strategies	Payoffs
Transactional	<ul style="list-style-type: none"> <li>• Most new customers start in this state (average relationship length 3.9 years)</li> <li>• Makes up 50% or more of the customer portfolio; little engagement beyond transactions; low levels of sales and sales growth</li> <li>• Low levels of trust, commitment, norms, and dependence</li> </ul>	<ul style="list-style-type: none"> <li>• <i>Check in periodically:</i> These customers benefit from periodic check-ins by a customer representative; do not assume business as usual.</li> <li>• <i>Look for inside sales:</i> Customers can be fertile targets for inside-sales growth through new product or service offerings to increase firm's potential value to customer.</li> </ul>	<ul style="list-style-type: none"> <li>• <i>Higher sales growth:</i> Moving a transactional customer to the transitional state can increase account sales by 400%–500%, creating 23% annual sales growth in our sample.</li> <li>• <i>Fewer Damaged Customers:</i> Mitigates the 15% probability of damaging a relationship.</li> </ul>
Transitional	<ul style="list-style-type: none"> <li>• Stems exclusively from transactional relationships; highest sales growth (more than three times average sales growth in our sample); medium level of sales</li> <li>• Roughly 1 in 10 customers comprise this active and “high-maintenance” portion of customer portfolio with high potential toward the communal state</li> <li>• Medium levels of trust, commitment, and norms; low levels of dependence</li> </ul>	<ul style="list-style-type: none"> <li>• <i>Dedicate account managers:</i> Customers' high potentials mandate dedicated lines of communication, as well as understanding of evolving customer needs, to combat competitive overtures.</li> <li>• <i>Invest in infrastructure:</i> Consider allocating specific resources to transitional customers. This helps customers realize their potential as well as increases switching costs through structural dependences.</li> </ul>	<ul style="list-style-type: none"> <li>• <i>Larger account sizes:</i> Converting transitional customers into communal customers increases account sizes by 33% (&gt;\$200,000/year) on average in our sample.</li> <li>• <i>Increased customer loyalty:</i> Customers in the communal state are 140% more likely to remain good customers in the following year than customers in the transitional state.</li> </ul>
Communal	<ul style="list-style-type: none"> <li>• The biggest, most profitable, and oldest customers; stems mostly from the transitional state; highest revenue (30% larger than average account sizes), with high and steady growth</li> <li>• Makes up the ~20% of customer portfolio that drives ~80% of sales</li> <li>• Fully interlocked for long-term relationship with highest levels of trust, commitment, norms, and dependence</li> </ul>	<ul style="list-style-type: none"> <li>• <i>Avoid inadvertent neglect:</i> Maintain diligent communication and regular assessment of dedicated resources for communal customers; do not take their business for granted.</li> <li>• <i>Actively prevent betrayal:</i> Regularly assess ex ante negotiations and contracts for potential areas of conflict and ex post fairness of business procedures, in addition to distribution of profits.</li> </ul>	<ul style="list-style-type: none"> <li>• <i>Higher profitability:</i> Growing and maintaining communal customers is associated with higher profitability through capitalization of value-producing channel opportunities. A 1% increase in the number of communal customers translates to a \$4.5 million increase in revenue in our sample.</li> <li>• <i>Amortization of costs:</i> Communal customers increase profitability by having longer customer tenure to amortize costs of dedicated seller investments.</li> </ul>
Damaged	<ul style="list-style-type: none"> <li>• Makes up 10%–15% of customer portfolio; medium account size; negative sales growth</li> <li>• 50% of newly damaged relationships were communal relationships that transitioned because of a sense of injustice or conflict</li> <li>• Lowest levels of trust, commitment, and norms; high dependence; likely to leave if replacement partners are available</li> </ul>	<ul style="list-style-type: none"> <li>• <i>Change course:</i> Assign a new customer representative or account recovery specialist to reassess terms of business and encourage identification areas of conflict and/or injustice.</li> <li>• <i>Compromise:</i> If warranted, provide concessions to alleviate conflict and feelings of injustice. This could be particularly important for formerly communal customers.</li> </ul>	<ul style="list-style-type: none"> <li>• <i>Improved reputation:</i> Recovering damaged relationships reduces negative word of mouth from disgruntled customers, improves the firm's ability to attract new accounts, and provides opportunity to learn from mistakes.</li> <li>• <i>Reduced customer churn:</i> On average, it costs five times more to acquire a new customer than to keep a current one, and a 5% reduction in churn can increase profits by 25% or more.</li> </ul>

managers can expediently identify the current relationship state of each customer.

Next, we provide dynamic relationship marketing migration strategies for each state that are actionable recommendations to managers once they have identified customers' relationship states. For example, for those customers currently in the highly profitable communal state, managers need to avoid neglect by maintaining regular communication and dedicating resources and customer-specific investments to maintain the relationships. More importantly, managers need to actively prevent betrayal by regularly assessing negotiations and contracts for potential areas of conflict before each transaction and fairness of business procedures and distribution of profits after each transaction. If there is inadvertent action that could be perceived as unfair by the customer, managers need to quickly react and compromise before the communal relationship spirals downward to a damaged one.

Finally, we describe the potential payoffs that managers can expect to achieve with the RM strategy deployment. To illustrate, for customers in the transitional state, the firm can provide a dedicated account manager to facilitate communication and guide investment in customer-specific resources to help convert these customers into communal relationships, which are associated with substantial increases in account sizes (by an average of 33%, or more than \$200,000 a year in our sample) and loyalty (by as much as 140%). Likewise, an actively reconciliatory RM strategy for customers in the damaged state can revive these relationships back to the transactional state, which results in reduced customer churn, improved reputation for future potential customers, and savings from new customer acquisition cost.

### **Limitations and Further Research**

We note some limitations of our research and suggest avenues for future investigation. We examine relationships between a single, large B2B firm and its many customers across a variety of product categories. Although we control for time-variant and time-invariant heterogeneity, the

generalizability of this analysis could be enhanced further with a broader sample of relationships from multiple selling firms in different industries, which could strengthen the robustness of inherently noisy approaches like HMM. Research might determine whether relationship moderators persist across different industries or business environments. Moreover, we examine four key relationship state variables that capture the lion's share of relationship quality according to extant research, but other state variables might capture additional facets and result in more nuanced states. For example, gratitude and reciprocity debts could be critical early in a relationship. Business relationships tend to be slow to develop (Jap and Anderson 2007), but using monthly or quarterly measurements might provide more fine-grained information about relationship dynamics and detect rapid migrations, especially early in a relationship and during conflict-laden periods. In addition, we have customer information with respect to one seller but not any competitive relationships. Further research should expand the analyses by noting the possible influences of third parties or group-level relationship dynamics. The collection of six years of longitudinal survey data on relationship constructs is a major undertaking, enabling us to study relationship dynamics empirically. The relationship health states we have presented are relative in the six-year window and might not represent the full spectrum of the relationship life cycle. As we expected, not all firms exhibited the same amount of movement during the six-year window. In aggregate, customers spend half of their time in a transactional state, and many do not appear to have had enough time or dynamics during this window to migrate out of the transactional state (see Table 4). With the increasing ease of data collection, further research with more comprehensive and longer-duration data across multiple firms might be able to model relationships from initiation to dissolution and thereby increase generalizability and paint a more detailed picture of relationship dynamics.

---

## **REFERENCES**

- Anderson, Erin and Barton Weitz (1992), "The Use of Pledges to Build and Sustain Commitment in Distribution Channels," *Journal of Marketing Research*, 29 (February), 18–34.
- Anderson, James C. and James A. Narus (1991), "Partnering as a Focused Market Strategy," *California Management Review*, 33 (Spring), 95–113.
- Ascarza, Eva and Bruce G.S. Hardie (2013), "A Joint Model of Usage and Churn in Contractual Settings," *Marketing Science*, 32 (July/August), 570–90.
- Brown, James R., Chekitan S. Dev, and Dong-Jin Lee (2000), "Managing Marketing Channel Opportunism: The Efficacy of Alternative Governance Mechanisms," *Journal of Marketing*, 64 (April), 51–65.
- Campbell, Margaret C. (1999), "Perceptions of Price Unfairness: Antecedents and Consequences," *Journal of Marketing Research*, 36 (May), 187–99.
- Cannon, Joseph P., Ravi S. Achrol, and Gregory P. Gundlach (2000), "When Does Vertical Coordination Improve Industrial Purchasing Relationships?" *Journal of Marketing*, 64 (October), 52–65.
- Celuch, Kevin G., John H. Bantham, and Chickery J. Kasouf (2006), "An Extension of the Marriage Metaphor in Buyer–Seller Relationships: An Exploration of Individual Level Process Dynamics," *Journal of Business Research*, 59 (May), 573–81.
- Dant, Rajiv P. and Patrick L. Schul (1992), "Conflict Resolution Processes in Contractual Channels of Distribution," *Journal of Marketing*, 56 (January), 38–54.
- De Wulf, Kristof, Gaby Odekerken-Schröder, and Dawn Iacobucci (2001), "Investments in Consumer Relationships: A Cross-Country and Cross-Industry Exploration," *Journal of Marketing*, 65 (October), 33–50.
- Dwyer, F. Robert and Rosemary R. LaGace (1986), "On the Nature and Role of Buyer–Seller Trust," in *AMA Summer Educators Conference Proceedings*, Vol. 11. Chicago: American Marketing Association, 40–45.
- , Paul H. Schurr, and Sejo Oh (1987), "Developing Buyer–Seller Relationships," *Journal of Marketing*, 51 (April), 11–27.

- Eyuboglu, Nermin and Andreas Buja (2007), "Quasi-Darwinian Selection in Marketing Relationships," *Journal of Marketing*, 71 (October), 48–62.
- Fang, Eric, Robert W. Palmatier, Lisa K. Scheer, and Ning Li (2008), "Trust at Different Organizational Levels," *Journal of Marketing*, 72 (March), 80–98.
- Fornell, Claes and David F. Larcker (1981), "Evaluating Structural Equation Models with Unobservable Variables and Measurement Error," *Journal of Marketing Research*, 18 (February), 39–50.
- Frazier, Gary L. (1983), "Inter-Organizational Exchange Behavior in Marketing Channels: A Broadened Perspective," *Journal of Marketing*, 47 (Fall), 68–78.
- Ganesan, Shankar (1993), "Negotiation Strategies and the Nature of Channel Relationships," *Journal of Marketing Research*, 30 (May), 183–203.
- Garbarino, Ellen and Mark S. Johnson (1999), "The Different Roles of Satisfaction, Trust, and Commitment in Customer Relationships," *Journal of Marketing*, 63 (April), 70–87.
- Gartner Research (2013), "Market Snapshot: Customer Relationship Management, Worldwide, 2012," (May 30), [available at <https://www.gartner.com/doc/2501215/market-snapshot-customer-relationship-management>].
- Gouldner, Alvin W. (1960), "The Norm of Reciprocity: A Preliminary Statement," *American Sociological Review*, 25 (2), 161–78.
- Grégoire, Yany and Robert J. Fisher (2008), "Customer Betrayal and Retaliation: When Your Best Customers Become Your Worst Enemies," *Journal of the Academy of Marketing Science*, 36 (Summer), 247–61.
- Gundlach, Gregory T., Ravi S. Achrol, and John T. Mentzer (1995), "The Structure of Commitment in Exchange," *Journal of Marketing*, 59 (January), 78–92.
- Hamilton, James D. (1989), "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle," *Econometrica*, 57 (March), 357–84.
- Heide, Jan B. (1994), "Interorganizational Governance in Marketing Channels," *Journal of Marketing*, 58 (January), 71–85.
- and George John (1990), "Alliances in Industrial Purchasing: The Determinants of Joint Action in Buyer–Supplier Relationships," *Journal of Marketing Research*, 27 (February), 24–36.
- and ——— (1992), "Do Norms Matter in Marketing Relationships?" *Journal of Marketing*, 56 (April), 32–44.
- Hibbard, Jonathan D., Nirmalya Kumar, and Louis W. Stern (2001), "Examining the Impact of Destructive Acts in Marketing Channel Relationships," *Journal of Marketing*, 38 (February), 45–61.
- Jap, Sandy D. and Erin Anderson (2007), "Testing a Life-Cycle Theory of Cooperative Interorganizational Relationships: Movement Across Stages and Performance," *Management Science*, 53 (February), 260–75.
- and Shankar Ganesan (2000), "Control Mechanisms and the Relationship Life Cycle: Implications for Safeguarding Specific Investments and Developing Commitment," *Journal of Marketing Research*, 37 (May), 227–45.
- Johnson, Michael D. and Fred Selnes (2004), "Customer Portfolio Management: Toward a Dynamic Theory of Exchange Relationships," *Journal of Marketing*, 68 (April), 1–17.
- Joshi, Ashwin W. (2009), "Continuous Supplier Performance Improvement: Effects of Collaborative Communication and Control," *Journal of Marketing*, 73 (January), 133–50.
- Kahn, Barbara (1998), "Variety: From the Consumer's Perspective," *Product Variety Management*, 10 (January), 19–37.
- Kaufmann, Patrick J. and Louis W. Stern (1988), "Relational Exchange Norms, Perceptions of Unfairness, and Retained Hostility in Commercial Litigation," *Journal of Conflict Resolution*, 32 (September), 534–52.
- Koza, Karen L. and Rajiv P. Dant (2007), "Effects of Relationship Climate, Control Mechanism, and Communications on Conflict Resolution Behavior and Performance Outcomes," *Journal of Retailing*, 83 (August), 279–96.
- Kozlenkova, Irina V., Stephen A. Samaha, and Robert W. Palmatier (2013), "Resource-Based Theory in Marketing," *Journal of the Academy of Marketing Science*, 6 (April), 1–21.
- Kumar, Nirmalya, Lisa K. Scheer, and Jan-Benedict E.M. Steenkamp (1995), "The Effects of Perceived Interdependence on Dealer Attitudes," *Journal of Marketing Research*, 32 (August), 348–56.
- Langfred, Claus W. (2007), "The Downside of Self-Management: A Longitudinal Study of the Effects of Conflict on Trust, Autonomy, and Task Interdependence in Self-Managing Teams," *Academy of Management Journal*, 50 (August), 885–900.
- Larzelere, Robert E. and Ted Huston (1980), "The Dyadic Trust Scale: Toward Understanding Interpersonal Trust in Close Relationships," *Journal of Marriage and the Family*, 42 (August), 595–604.
- Li, Shibo, Baohong Sun, and Alan L. Montgomery (2011), "Cross-Selling the Right Product to the Right Customer at the Right Time," *Journal of Marketing Research*, 48 (August), 683–700.
- Luo, Anita and V. Kumar (2013), "Recovering Hidden Buyer–Seller Relationship States to Measure the Return on Marketing Investment in Business-to-Business Markets," *Journal of Marketing Research*, 50 (February), 143–60.
- MacDonald, Iain L. and Walter Zucchini (1997), *Hidden Markov and Other Models for Discrete-Valued Time Series*. New York: CRC Press.
- Mohr, Jakki J., Robert J. Fisher, and John R. Nevin (1996), "Collaborative Communication in Interfirm Relationships: Moderating Effects of Integration and Control," *Journal of Marketing*, 60 (July), 103–15.
- Montoya, R., O. Netzer, and K. Jedidi (2010), "Dynamic Allocation of Pharmaceutical Detailing and Sampling for Long-Term Profitability," *Marketing Science*, 29 (5), 909–24.
- Moorman, Christine, Gerald Zaltman, and Rohit Deshpandé (1992), "Relationships Between Providers and Users of Market Research: The Dynamics of Trust Within and Between Organizations," *Journal of Marketing Research*, 29 (August), 314–29.
- Morgan, Robert M. and Shelby D. Hunt (1994), "The Commitment-Trust Theory of Relationship Marketing," *Journal of Marketing*, 58 (July), 20–38.
- Mullins, Ryan R., Michael Ahearne, Son K. Lam, Zachary R. Hall, and Jeffrey P. Boichuk (2014), "Know Your Customer: How Salesperson Perceptions of Customer Relationship Quality Form and Impact Account Profitability," *Journal of Marketing*, 78 (November), 38–58.
- Netzer, Oded, James M. Lattin, and Vikram Srinivasan (2008), "A Hidden Markov Model of Customer Relationship Dynamics," *Marketing Science*, 27 (March/April), 185–204.
- Palmatier, Robert W., Rajiv P. Dant, and Dhruv Grewal (2007), "A Comparative Longitudinal Analysis of Theoretical Perspectives of Interorganizational Relationship Performance," *Journal of Marketing*, 71 (October), 172–94.
- , ———, ———, and Kenneth R. Evans (2006), "Factors Influencing the Effectiveness of Relationship Marketing: A Meta-Analysis," *Journal of Marketing*, 70 (October), 136–53.

- , Mark B. Houston, Rajiv P. Dant, and Dhruv Grewal (2013), "Relationship Velocity: Toward a Theory of Relationship Dynamics," *Journal of Marketing*, 77 (January), 13–30.
- , Lisa K. Scheer, Kenneth R. Evans, and Todd J. Arnold (2008), "Achieving Relationship Marketing Effectiveness in Business-to-Business Exchanges," *Journal of the Academy of Marketing Science*, 36 (Summer), 174–90.
- Ping, Robert A. (1999), "Unexplored Antecedents of Exiting in a Marketing Channel," *Journal of Retailing*, 75 (Summer), 218–41.
- Rahim, M. Afzalur (2002), "Toward a Theory of Managing Organizational Conflict," *International Journal of Conflict Management*, 13 (3), 206–35.
- Rindfleisch, Aric and Jan B. Heide (1997), "Transaction Cost Analysis: Past, Present, and Future Applications," *Journal of Marketing*, 61 (October), 30–54.
- Ring, Peter Smith and Andrew H. Van de Ven (1994), "Developmental Processes of Cooperative Interorganizational Relationships," *Academy of Management Review*, 19 (January), 90–118.
- Rousseau, Denise M., Sim B. Sitkin, Ronald S. Burt, and Colin Camerer (1998), "Not So Different After All: A Cross-Discipline View of Trust," *Academy of Management Review*, 23 (July), 393–404.
- Rusbult, Caryl E., Isabella M. Zembrodt, and Lawanna K. Gunn (1982), "Exit, Voice, Loyalty, and Neglect: Responses to Dissatisfaction in Romantic Involvements," *Journal of Personality and Social Psychology*, 43 (December), 1230–42.
- Samaha, Stephen A., Joshua T. Beck, and Robert W. Palmatier (2014), "The Role of Culture in International Relationship Marketing," *Journal of Marketing*, 78 (September), 78–98.
- , Robert W. Palmatier, and Rajiv P. Dant (2011), "Poisoning Relationships: Perceived Unfairness in Channels of Distribution," *Journal of Marketing*, 75 (May), 99–117.
- Scheer, Lisa K., C. Fred Miao, and Robert W. Palmatier (2015), "Dependence and Interdependence in Marketing Relationships: Meta-Analytic Insights," *Journal of the Academy of Marketing Science*, 43 (November), 694–712.
- Schweidel, David A., Eric T. Bradlow, and Peter S. Fader (2011), "Portfolio Dynamics for Customers of a Multiservice Provider," *Management Science*, 57 (3), 471–86.
- Wathne, Kenneth H. and Jan B. Heide (2000), "Opportunism in Interfirm Relationships: Forms, Outcomes, and Solutions," *Journal of Marketing*, 64 (October), 36–51.
- Wilson, David T. (1995), "An Integrated Model of Buyer–Seller Relationships," *Journal of the Academy of Marketing Science*, 23 (Fall), 335–45.
- Zhang, Jonathan Z., Oded Netzer, and Asim Ansari (2014), "Dynamic Targeted Pricing in B2B Relationships," *Marketing Science*, 33 (May/June), 317–37.