Robert W. Palmatier, Mark B. Houston, Rajiv P. Dant, & Dhruv Grewal

Relationship Velocity: Toward A Theory of Relationship Dynamics

The dynamic components of relational constructs should play an important role in driving performance. To take an initial step toward a theory of relationship dynamics, the authors introduce the construct of commitment velocity—or the rate and direction of change in commitment—and articulate its important role in understanding relationships. In two studies, the authors demonstrate that commitment velocity has a strong impact on performance, beyond the impact of the level of commitment. In Study 1, modeling six years of longitudinal data in a latent growth curve analysis, the authors empirically demonstrate the significance of commitment velocity as a predictor of performance. In Study 2, the authors use matched multiple-source data to investigate the drivers of commitment velocity. Both customer trust and dynamic capabilities for creating value through exchange relationships (i.e., communication capabilities for exploring and investment capabilities for exploiting opportunities) affect commitment velocity. However, trust and communication capabilities become less impactful as a relationship ages, while investment capabilities grow more important. The authors offer three post hoc tenets that represent initial components of a theory of relationship dynamics that integrates two streams of relationship marketing research into a unified perspective.

Keywords: relationship velocity, latent growth curve, life cycle, commitment velocity, theory of relationship dynamics

Scholars and managers generally agree that relationships between firms evolve over time and are fundamentally dynamic. In a seminal article, Dwyer, Schurr, and Oh (1987) argue that relationships operate differently as they develop over time (e.g., grow, mature, decay). Thus, researchers often use discrete "stages" or the "relationship age" to identify empirical differences in exchanges as relationships follow a typical life cycle (Heide 1994; Hibbard et al. 2001; Jap and Anderson 2007; Jap and Ganesan 2000). However, most studies still describe a relationship using a static snapshot of the "level" of relational constructs (Palmatier et al. 2006). For example, Morgan and Hunt (1994) focus on the key relational variables of trust and commitment but use only the customer's perceived levels of these variables to capture the current state of an exchange. There are several potential shortcomings of such a static perspective; in particular, as Grayson and Ambler (1999, p. 139) note, "the length of the relationship changes the nature of the associations between relational constructs," and "the exact nature of these relational dynamics remain elusive."

Robert W. Palmatier is Professor of Marketing and John C. Narver Chair in Business Administration, University of Washington (e-mail: palmatrw@uw.edu). Mark B. Houston is Eunice and James L. West Chair of American Enterprise, Neeley School of Business, Texas Christian University (e-mail: m.b.houston@tcu.edu). Rajiv P. Dant is Professor of Marketing and Michael F. Price Chair in Business, Price College of Business, University of Oklahoma (e-mail: rdant@ou.edu). Dhruv Grewal is Toyota Professor of e-Commerce and Electronic Business and Professor of Marketing, Babson College (e-mail: dgrewal@babson.edu). The authors thank the Marketing Science Institute for their support of this research. Thanks also to the faculties at Duke University and University of Washington for their input into this project. Inge Geyskens served as area editor for this article.

We offer a reconceptualization of relationship state, or the description of the precise condition of a relationship at a specific point in time, that modifies the fundamental nature of extant theoretical frameworks (which offer level-only views). We introduce and ascribe key roles for the dynamic components of relational constructs that explicitly capture changes over time—essential for understanding exchange outcomes. Starting with the key construct of commitment, we take an initial step in building a theory of relationship dynamics by introducing the construct of commitment velocity, or the rate and direction of change in commitment. Both the level and velocity components are critical for understanding exchange performance. Research in psychology, marriage, and marketing all support the premise that commitment velocity provides critical, performance-relevant information. For example, research on human responses to trends (e.g., Johnson, Tellis, and MacInnis 2005; Kahneman and Tversky 1972), including trends in interpersonal relationships (Huston et al. 2001), indicates that relationship growth is salient for customer decisions and behaviors.

After developing theoretical support for the significance of the dynamic aspects of relational variables, we empirically investigate commitment velocity in two studies. In Study 1, for 433 newly formed channel relationships, we model customers' commitment using longitudinal data and a latent growth curve approach that enables us to assess the effects of both static (level) and dynamic (velocity) components of relationship state on performance. We measure commitment velocity directly with a new multi-item scale in Study 2 using a different sample of 380 matched customer–salesperson–selling firm triads from multiple firms. Study 2 adds to the generalizability of our findings (with multiple firms whose relationships vary widely in age and a direct

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measure of commitment velocity) and situates commitment velocity in a nomological framework to understand its drivers.

Overall, we contribute to the theory and practice of relationship marketing in three key ways. First, we provide theoretical and empirical foundations for a dynamic model of relationship marketing by integrating static and dynamic components of commitment into extant models; thus, we address a key research question: *What role does the dynamic component of relationship commitment play in relationship marketing?* Our results support the notion that commitment velocity matters because it has a significant influence on sales performance (Studies 1 and 2), beyond the impact of the static level of commitment. When we add commitment velocity to the model, the effect of the commitment level on sales performance often becomes insignificant, indicating that velocity may provide more performance-relevant information than level (as typically measured in extant research). Our investigation of relational dynamics also addresses a key gap noted by Lewicki, Tomlinson, and Gillespie (2006, p. 991), namely, that little attention focuses on "conceptualizing and measuring" relationship "development over time"; instead, most research "has taken a static, 'snapshot' view" of relationships.

Second, because commitment velocity is a dynamic, rather than static, construct, we draw on dynamic capabilities research (Morgan and Slotegraaf 2012; Teece, Pisano, and Shuen 1997) to address another question: *What factors drive commitment velocity, and how do these effects vary as the relationship develops or across different environments?* The results show that trust, communication, and investment capabilities influence commitment velocity; capabilities drive velocity by enabling the continual exploration (through communication) and exploitation (through investment) of opportunities (March 1991). Yet trust and communication capabilities have less impact as a relationship matures, whereas investment capabilities become more important. Communication capabilities are most critical when industry turbulence is high.

Third, this study takes an initial theory-building step to help integrate two vital but distinct streams of relationship research. One stream suggests a key mediating role of commitment (and its antecedent, trust) to capture the relational content of an exchange and drive performance (e.g., Morgan and Hunt 1994; Palmatier et al. 2006). The other stresses the developmental, path-dependent nature of business relationships, such that the linkages among antecedents, mediators, and consequences vary across life cycle stages or over time (Dwyer, Schurr, and Oh 1987; Heide 1994; Jap and Anderson 2007). Commitment velocity extends key relational mediator research by adding a dynamic component to commitment. Building on extant research and our results, we offer three post hoc tenets to help spur progress toward a theory of relationship dynamics that can integrate the two streams into a unified perspective.

Commitment Velocity

Theoretical Support for the Role of Commitment Velocity

Relationships, whether between firms or individuals, are not static phenomena. Instead, over time and through repeated interactions, relationships develop, mature, and decline—in short, change is typical (Dwyer, Schurr, and Oh 1987; Jap and Anderson 2007; Jap and Ganesan 2000). However, extant research often fails to account for the information contained in a relationship's trajectory and instead focuses mainly on the *level* of relational constructs (Palmatier et al. 2006). We offer the term "relationship velocity" to encompass both the rate and direction of changes in relational constructs (e.g., trust, commitment, norms) and thereby capture the dynamic aspect of such constructs. Specifically, we focus on commitment velocity, or the rate and the direction of change in commitment, because commitment (i.e., the enduring desire to maintain a valued relationship) is perhaps the most critical factor for predicting performance (Palmatier et al. 2006). For example, Morgan and Hunt (1994, p. 23) propose "commitment among exchange partners as key to achieving valuable outcomes," and Gundlach, Achrol, and Mentzer (1995, p. 78) argue that commitment is the "essential ingredient for successful long-term relationships."

Our focus on velocity as a dynamic measure of commitment reflects our expectation that both the rate and the direction of change will be critical to future performance. "Rate" indicates the magnitude of the change, and "direction" indicates whether the relationship is growing or declining. Consistent with this perspective, Jap and Anderson (2007, p. 272) report post hoc observations that some relationships with low but stable levels of relational constructs "can linger for surprisingly long times," whereas other firms with rapidly worsening (i.e., high negative velocity) relationships go "into a flurry of activity" to investigate new partners.

Because relationships are fundamentally dynamic phenomena, commitment velocity should offer critical information. We propose that customers' implicit mental models of relationships include both the level and the velocity of commitment, which define their decision heuristics. This potential role of velocity in decision making receives support from two research domains that reveal basic human decision biases regarding perceived change and a specific role for relationship change in interpersonal relationships.

First, insights into how velocity might affect a customer's decisions derive from research into the human tendency to identify trends and use those insights to make decisions (Johnson, Tellis, and MacInnis 2005; Kahneman and Tversky 1972). According to basic psychological tendencies, predictions based on trends are powerful and highly resistant to change (Koriat, Fiedler, and Bjork 2006). People routinely engage in "trend extrapolation," projecting trends (both rate and direction) into the future and making decisions with the assumption that those trends will continue (Johnson, Tellis, and MacInnis 2005). Trend extrapolation operates as an unconscious heuristic, and perception biases reinforce trend-based heuristics, such that people detect and attribute causality to evidence that supports their expectations but reject contrary information (Koriat, Fiedler, and Bjork 2006).

Second, research into relationship formation and dissolution processes suggests an important role for relationship change in influencing attitudes and behaviors. For example, in an interpersonal setting, "the realization that one's mate has become less affectionate ... may be more important than the mate's current level of affectional expression" (Huston et al. 2001, p. 238). Both gain–loss and social exchange theorists demonstrate that the duration of a relationship relates more to changes in, rather than the levels of, relationships (Aronson 1969). People are also more sensitive to perceived changes, even when such sensitivity is suboptimal from a rational cost–benefit standpoint. As Aronson (1969, p. 150) concludes, "a person whose esteem for us increases over time will be liked better than one who has always liked us. This would be true even if the number of rewards were greater in the latter case." Moreover, Fincham and Bradbury (1992) demonstrate that when partners perceive their relationship to be on a downward slope, they make dispositional rather than situational attributions. Consistent with this evidence, we expect customers to use commitment velocity as an important decision heuristic.

Differences and Similarities in Relationship Life Cycle, Age, and Velocity Perspectives

The velocity concept is consistent with both relationship age and life cycle perspectives, which suggests that as a relationship ages, it follows a common trajectory: from an exploratory stage through expansion, maturity, and decline. The trajectory reflects the underlying processes by which relational constructs evolve (Dwyer, Schurr, and Oh 1987; Jap and Ganesan 2000). Relationship life cycle perspectives explicitly recognize that relationship formation is a "developmental process" and that relationships follow a path-dependent trajectory (Ring and Van de Ven 1994, p. 112), albeit in a discrete categorical sense. Researchers use "stages" as epistemological devices to describe differences over time in what is most likely a continuous process; it is difficult to argue that a relationship changes instantaneously at a fixed boundary when it moves from one stage to the next.

Alternatively, relationship-age perspectives use age as a continuous proxy for progress through developmental stages (Hibbard et al. 2001; Jap and Anderson 2007; Lusch and Brown 1996). However, the age perspective differs from the life cycle stage view by assuming that all relationships move through the developmental cycle at the same rate (i.e., ignoring temporal heterogeneity). Age as an indicator of relationship development thus implies that all ten-year-old relationships are at the same developmental stage, disregarding any differences in growth rates (Eggert, Ulaga, and Schulz 2006). In contrast, a life cycle view recognizes that relationships move through stages at different rates, but it divides the relationship trajectory into discrete segments, so all relationships within one stage represent the same developmental state until they move into the next homogenous stage. Table 1 summarizes the extant literature that reflects both life cycle and age perspectives.

Measuring the level and velocity of commitment offers an alternative way to capture the essence of developmental stages in a continuous manner. For example, consider that most life cycle– or age-based research suggests that relationships follow an inverted U-shaped trajectory and pass through sequential stages, such that relationship performance depends on the position on the curve (Dwyer, Schurr, and Oh 1987; Heide 1994; Hibbard et al. 2001; Jap and Ganesan 2000). A consistent but alternative perspective would propose that relationships follow a continuous growth trajectory, determined by their underlying developmental processes, so that performance depends on the level and velocity of commitment at any point in time. In a typical exchange, then, initial commitment velocity might be positive, with a slow rate of change in the exploration stage. The rate of change may increase as the relationship moves into the expansion stage, but then velocity decays as the relationship peaks in the maturity stage. Ultimately, it even becomes negative as the relationships declines. At each point, the relationship state, or the description of the precise condition of a relationship at a specific point in time, can be captured by the level and velocity of commitment.

The velocity perspective thus advantageously supports a continuous indicator of relationship development (in contrast to the life cycle approach but consistent with the relationship-age approach), supports heterogeneous and cyclical development rates (in contrast to the relationship-age approach but consistent with the life cycle approach), and uses both static and dynamic components of the relationship state. In addition, treating commitment velocity as a latent construct in a conceptual model supports efforts to model its antecedents and outcomes, something that is not viable when velocity (i.e., change or slope) appears as an interaction with age or stage rather than as a construct.

Study 1: Dynamic Model of Relationships

Study 1 has two key objectives regarding our first research question—What role does the dynamic component of relationship commitment play in relationship marketing? First, consistent with all three dynamic relationship perspectives, we test whether relationship commitment follows a common trajectory.[1] Second, we test the premise that commitment velocity affects sales performance beyond the effect of commitment level.

Even though all three dynamic relationship perspectives (stage, age, velocity) argue that relationships in similar environments follow a common growth trajectory, empirical testing of the underlying premise of a common relationship growth trajectory (versus a random walk) is noticeably absent from prior literature. To address this concern, we mimic a latent growth curve approach that Bollen and Curran (2006) apply in an education context to isolate and test empirically for the presence (or absence) of an underlying growth process. For example, most students follow a common growth curve: Learning the alphabet provides a foundation for reading words, which are necessary to form sen-

[1]Relationship life cycle, age, and velocity perspectives are all based on a single underlying premise: Relationships follow a common developmental process that typically results in similar trajectories, not a "random walk" process (e.g., Jap and Anderson [2007] report that 77% of the dyads in their sample follow a common path).

TABLE 1
Summary of Illustrative Research Based on Life Cycle and Age Perspectives of Relationship Development

Reference	Empirical Approach	Description for Life Cycle Stages and Ages	Key Relational Variables Studied	Description of Relationship Development Trajectory	Expectations (for Conceptual Papers)/Findings (for Empirical Papers) Regarding Relational Variables Across Life Cycle/Age
Dwyer, Schurr, and Oh (1987)	Conceptual	Awareness–exploration–expansion–commitment–dissolution	Bilateral communication, goal congruence, trust, norms, joint satisfaction	Inverted U shape	Communication and the development of norms provide a dynamic basis for the emergence of trust, continued interaction, goal alignment, and satisfaction. The relational constructs move in concert through the phases.
Ring and Van de Ven (1994)	Conceptual	Negotiation–agreement–execution–assessment–dissolution	Relational norms, trust, mutual dependence, idiosyncratic investments, communication	Inverted U shape, with possibility of cyclical iterations	"The developmental processes ... explain how cooperative [interorganizational relationships] emerge, evolve, and dissolve over time" (p. 112). The relational constructs move in concert through the phases.
Heide (1994)	Conceptual and partial empirical test	Initiation–maintenance–termination	Mutual dependence, bilateral (relational) governance	Inverted U shape	"Governance is a multidimensional phenomenon, encompassing the initiation, termination, and ongoing relationship maintenance between a set of parties" (p. 72). Mutual dependence leads to relational governance.
Wilson (1995)	Conceptual; insights from ethnography	Partner selection–defining purpose–settling relationship boundaries–creating relationship value–relationship maintenance	Social bonds, mutual goals, satisfaction, trust, cooperation	Linear increase (destabilization or dissolution is noted as a future research direction)	Trust, social bonds, mutual goals, and power/dependence issues are more important in early stages. These constructs provide a foundation from which commitment, cooperation, adaptation, and structural bonds grow in later stages.
Lewicki and Bunker (1996)	Conceptual	Stage 1 (calculus- and deterrence-based trust)–Stage 2 (knowledge-based trust)–Stage 3 (identification-based trust)–decline	Trust, identification	Stepped (S-shaped) increase; declines may or may not be permanent	"In professional relationships, trust develops gradually as the parties move from one stage to another" (p. 124). Experience with partner allows the basis of trust to evolve, from mere cost–benefit calculations, to knowledge of the partner, to identification with the partner.
Rousseau et al. (1998)	Conceptual	Early (dominated by calculative and institutional trust)–middle–later (dominated by relational trust)	Trust	Relational trust increases in a linear way	"[T]rust changes over time—developing, building, declining, and even resurfacing in long-standing relationships" (p. 395). "Calculative trust" is replaced by "relational trust" as positive emotions are generated in response to a partner's reliability and dependability, over time.
Jap and Ganesan (2000)	Cross-sectional; age cohorts	Exploration–buildup–maturity–decline	Satisfaction, conflict, bilateral investments, relational norms, interdependence, commitment	Inverted U shape	"The contrast in results from the total sample to the phase-by-phase analysis underscores the powerful effect of relationship context in determining key relationship outcomes, and highlights the need for tailoring interorganizational strategies according to the relationship phase" (p. 241). The relational variables move in concert, but the impacts on commitment of bilateral investments, relational norms, and contracts differ across relationship stages.
Hibbard et al. (2001)	Cross-sectional; age as a covariate	Quartile 1 (age = 1–96 months)–Quartile 2 (age = 97–160 months)–Quartile 3 (age = 161–236 months)–Quartile 4 (age = 237+ months)	Trust, commitment, communication, shared values, mutual dependence	Part inverted U shape and part linear decreasing trend	"[Relationship marketing] yields diminishing returns over time" (p. 31). The impact on relationship performance of trust and communication follows an inverted U-shaped path across relationship quartiles; the impact on relationship performance of commitment, shared values, and dependence follow a linear decline.
Jap and Anderson (2007)	Cross-sectional; age cohorts	Compared Dwyer, Schurr, and Oh (1987) with Ring and Van de Ven (1994)	Goal congruence, information exchange, harmony, trust	Inverted U shape, with possibility of cyclical iterations	Most relationships follow Dwyer, Schurr, and Oh's (1987) predictions; those that cycle among stages have worse performance; goal congruence, information exchange, harmony, and trust move in concert.

tences, and so on. Each step is necessary to move to the next level. Consistent with extant life cycle and age research, we argue that commitment, on average, follows a common growth trajectory over time, rather than a random walk or a unique growth trajectory in each relationship (see Table 1). Therefore, relationship development requires building on previous interactions (e.g., dating, exploration stage) before moving to higher forms of interaction (e.g., marriage, cooperation, expansion stage). Researchers similarly argue that communication and the development of norms provide the basis for the emergence of trust, continued interaction, and ultimately commitment (Dwyer, Schurr, and Oh 1987; Ring and Van de Ven 1994). If a significant latent growth curve does not exist, we must reject the underlying premise of the three dynamic perspectives, namely, that relationships develop according to common underlying processes.

H_1: Relationship commitment typically follows a common developmental trajectory, as demonstrated by a significant latent growth curve (e.g., commitment velocity).

Effect of Commitment Level and Velocity on Sales Performance

A large body of research suggests that customers' decisions, behaviors, and performance depend on their commitment to a seller; commitment is positively linked to sales performance (Palmatier, Dant, and Grewal 2007). However, to our knowledge, no research has linked a change in commitment (i.e., velocity) to such outcomes.

Decision heuristic theory asserts that perceived trends can serve to appraise relationships, inform attributions, and determine subsequent behaviors (Johnson, Tellis, and MacInnis 2005; Koriat, Fiedler, and Bjork 2006). Accordingly, we argue that customers make decisions using both conscious and subconscious velocity-based heuristics. Decision makers in relationships with positive velocity behave as if the relationship will continue to grow at a similar rate and direction, so they act more strongly on the basis of their "growing" evaluations of commitment (Johnson, Tellis, and MacInnis 2005). These customers should be more sensitive to supportive evidence, reject contrary data, and act in self-fulfilling ways, which reinforces the positive effect of commitment velocity on their behaviors (Fincham and Bradbury 1992; Koriat, Fiedler, and Bjork 2006).

We posit that a customer in a relationship that is growing quickly (high positive velocity) makes decisions on the basis of the heuristic belief that this relationship will continue to grow quickly and thus be more likely to give more business to the focal exchange partner, adopt new products, and be more accepting of positive and less accepting of negative information. All these behaviors enhance sales performance, or the annual change in sales revenue, through share expansion, more new product sales, or less erosion of existing sales. In another relationship in which the customer has the same level of commitment but perceives that the relationship is decaying, he or she instead would behave in ways that hinder sales growth (e.g., shift business to another supplier, refuse to buy a new product). Prior research provides indirect evidence that the effects of relationships on outcomes depend on whether the relationship is perceived as growing or decaying (Jap and Anderson 2007).

H_2: Commitment (a) level and (b) velocity positively affect sales performance.

Sample and Measures

In this early exploration of the growth trajectories of business relationships, we attempt to limit extraneous sources of variation that might make it difficult to model the growth trajectory of commitment. Thus, to minimize variations in firm-level factors and competitive conditions, we focus on a single selling firm's portfolio of relationships with its channel partners. The sample for this research consists of channel relationships between a large North American *Fortune* 500 company (seller) and its channel members (customers) for a multitude of products, such as home appliances, tools, and clothing. We gathered data in six successive annual mail surveys, sent to senior managers of 1637 customer firms on average; the selling firm provided archival sales data. The average annual response rate over the six years was 53.4%. Few relationships (<2%) were terminated during this period.

Our study context offers a particular advantage for studying relationship development, in that the seller was implementing a new channel strategy and establishing many new relationships, which enabled us to capture data as relationships developed. However, because there was some variation in relationship age at the time of the first measurement wave (i.e., the seller took a few years to initiate connections with all new channel members), we transformed the data into an age-aligned sample. To align the sample by age, depending on when the relationship began, we transformed each case so that its first year aligned with "year 1" in our final sample. This transformation is critical for latent growth curve analysis because controlling only for age generates biased estimates (Mehta and West 2000). This transformation process, combined with incomplete responses from some informants, produced some missing data; we removed any cases with more than three years of missing data. We thus based our analysis on 433 seller–customer relationships. All analyses and references to age use the transformed, age-aligned sample (i.e., year 1 refers to the first year of each relationship).

We assessed nonresponse bias in multiple ways. First, we conducted comparisons of early and late informants for all measurement waves on all study constructs. Second, we compared cases included in the analysis with the total sample across each year of data collection on all five study constructs (as listed in Table 2). The results from both tests indicate that the respondents represented the same population ($p > .05$).

We used identical measures for each data collection wave; we report the items and their sources in the Appendix. We measured customer commitment, the only latent construct, with three items using a five-point Likert scale with an average coefficient alpha of .86, demonstrating good internal reliability. For the measure of sales performance, we used seller-provided sales growth (%) calculated from sales revenues ($) for the year subsequent to the

TABLE 2
Study 1: Descriptive Statistics and Correlations

Constructs	M	SD	α	1	2	3	4	5
1. Customer commitment	4.27	.63	.86	1.00				
2. Competitive distance	22.47	41.70	N.A.	–.08	1.00			
3. Customer size	5.04	6.05	N.A.	.01	.00	1.00		
4. Sales performance$_{t = 4–5}$	6.02	13.28	N.A.	–.17*	.01	–.01	1.00	
5. Sales performance$_{t = 6–7}$	–1.25	10.83	N.A.	.09	–.15*	.10	–.03	1.00

*$p < .05$.
Notes: α = coefficient alpha; N.A. = nonapplicable items.

period that we used to estimate the growth curves. Table 2 provides the descriptive statistics and correlations.

Method: Latent Growth Curve Analysis

A latent growth curve analysis is especially powerful for isolating and testing latent growth constructs that emerge from longitudinal data, based on underlying developmental phenomena (Bollen and Curran 2006). Specifically, it provides a statistical test to determine if sample relationships follow a common developmental path (e.g., life cycle stages), as described by latent growth parameters (e.g., velocity), or if each relationship develops following a unique or random path. Thus, this approach is particularly appropriate for our initial inquiry.

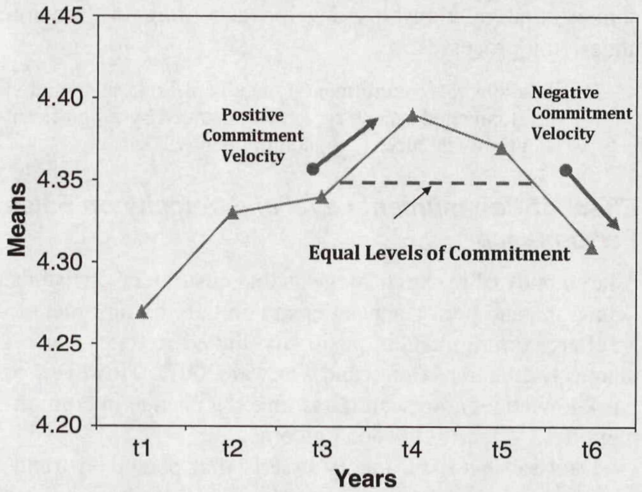
To understand how commitment evolves as relationships develop over time, latent growth curve modeling (LGCM) offers several advantages. From a conceptual perspective, LGCM supports the investigation of phenomena that change over time as a result of "the existence of *continuous underlying* or *latent trajectories* … [in which] the trajectory process is only observed indirectly using repeated measures" (Bollen and Curran 2006, p. 3, italics in original). Latent growth curve modeling can isolate and test for the significance of unobserved growth constructs due to a common developmental process; that is, using LGCM, we can test the premise that relationships develop along a common trajectory, which is a key, untested assumption of life cycle research. For example, previous methodological approaches using life cycle stages or age as a moderator to capture dynamic effects are unable to isolate and test velocity as a unique latent construct or determine if relationships develop following a continuous underlying process.

In Figure 1, we plot the overall sample means for commitment in the first six years of relationship development. Commitment switches from positive to negative velocity when the relationship is approximately four years old. To capture the curvilinear nature of commitment, we use a piecewise LGCM approach to capture the positive and negative velocity regions. Although the changes in the sample averages are relatively small, across time, changes in commitment for a specific relationship can be vast. For example, the change in the level of commitment ranges between –2.3 and 3.0 (five-point scale).

Analysis and Results

We estimate a piecewise LGCM for commitment by modeling the initial level (α) and velocity parameters (β_1 and β_2) as latent constructs, such that all factor loadings for the

FIGURE 1
Study 1: Change in Customer Commitment Over Time



Notes: Means for commitment reflect each of the first six years of the 433 interfirm relationships.

latent construct that represents commitment's initial level are fixed to 1. The factor loadings for the velocity of commitment (β_1) for the first segment are, sequentially, 0, 1, 2, 3, 3, and 3; the factor loadings for the velocity of commitment (β_2) for the second segment, sequentially, are 0, 0, 0, 0, 1, and 2, across the six years of commitment data (for a detailed description, see Bollen and Curran 2006). This piecewise approach can estimate two velocities, such that the velocity for the first segment (β_1) captures the growth in commitment from year 1 to year 4, and the velocity for the second segment (β_2) captures the decay in commitment from year 4 to year 6. The piecewise LGCM for commitment (Table 3) fits the data well; the mean of initial level of commitment ($\mu_\alpha = 4.24$, $p < .01$) and the mean of velocity$_{t = 1–4}$ ($\mu_{\beta 1} = .05$, $p < .01$) are both significant, whereas the mean of velocity$_{t = 4–6}$ ($\mu_{\beta 2} = –.03$, $p < .10$) is marginally significant. Thus, the results support H_1.[2]

Because our model features two velocities, consistent with our conceptualization, we include a path from each commitment level (period preceding performance) and

[2]Evaluations of LGCMs for commitment using other functional forms (no growth, linear growth, optimal growth) and different piecewise segments result in a worse-fitting model, which increases our confidence in our model specification.

TABLE 3
Study 1 Results: Test of Commitment's LGCM

Model	Fixed Effects μ_{α}	$\mu_{\beta 1}$	$\mu_{\beta 2}$	Random Effects $\psi_{\alpha\alpha}$	$\psi_{\beta 1\beta 1}$	$\psi_{\alpha\beta 1}$	$\psi_{\beta 2\beta 2}$	$\psi_{\alpha\beta 2}$	$\psi_{\beta 1\beta 2}$
Commitment Latent Growth Curve (H_1)									
Piecewise linear latent growth model	4.24**	.05**	−.03*	.23**	.03**	−.05**	.06**	−.01	−.01
	(.04)	(.02)	(.02)	(.04)	(.01)	(.02)	(.02)	(.02)	(.01)
$\chi^2_{(12)}$ = 12.86 (p > .10), IFI = .99, CFI = .99, and RMSEA = .01									

*p < .10.
**p < .01.
Notes: Unstandarized coefficients are reported with standard errors in parentheses. μ_{α} = mean of initial level, μ_{β} = mean of velocity, $\psi_{\alpha\alpha}$ = variance in initial level, $\psi_{\beta\beta}$ = variance in velocity, and $\psi_{\alpha\beta}$ = covariance between level and velocity. IFI = incremental fit index, CFI = confirmatory fit index, and RMSEA = root mean square error of approximation.

velocity to sales performance (measured in the year after the period used to estimate velocity), which provides two opportunities to test H_2. We test the effect of commitment velocity$_{t = 1–4}$ on sales growth during years 4 to 5 and the effect of commitment velocity$_{t = 4–6}$ on sales growth from years 6 to 7. Because other factors can affect relationship and sales growth, we also add paths from two relevant control variables to both commitment and performance variables: (1) competitive distance, which captures variance in performance due to the proximity of a competitor (miles), and (2) customer size, a proxy for customer purchasing power (number of employees).

This overall model fits the data well ($\chi^2_{(31)} = 36.14, p > .05$; comparative fit index [CFI] = .98, incremental fit index [IFI] = .98, and root mean square error of approximation [RMSEA] = .02). In Table 4, we report the results of the final model used to test H_2. The influence of the level of commitment$_{t = 4}$ on sales performance$_{t = 4–5}$ is not significant (β = –1.30, n.s.), but the level of commitment$_{t = 6}$ significantly affects sales performance$_{t = 6–7}$ ($\beta = 5.98, p < .01$), which provides partial support for H_{2a}. Regarding the effects of commitment velocity, we find significant effects for both commitment velocity$_{t = 1–4}$ on sales performance$_{t = 4–5}$ ($\beta = 18.10, p < .05$) and commitment velocity$_{t = 4–6}$ on sales performance$_{t = 6–7}$ ($\beta = 28.77, p < .05$), in support of H_{2b}.

However, LGCM has a few limitations. First, inferring velocity by observing changes across repeated measures, over time, requires multiple periods (i.e., three years or more) of longitudinal data. Maintaining access to respondents for a multiperiod study is challenging in settings in which employee turnover, changing management priorities, and changing budgetary and environmental factors disrupt the setting. Second, similar to structural equation modeling, interactions in LGCM are typically modeled by subdividing the sample into groups, which precludes testing the simultaneous effects of multiple moderated antecedents and often requires dichotomizing continuous variables. In Study 1, we use the strength of LGCM to isolate and test empirically for

TABLE 4
Study 1 Results: Dynamic Model of Relationships

Variables	Hypotheses (Directions)	Unstandardized Path Coefficients (SE)	Results
Commitment → Outcomes			
Commitment level$_{t = 4}$ → sales performance$_{t = 4 \text{ to } 5}$	H_{2a} (+)	−1.30 (1.67)	Rejected
Commitment level$_{t = 6}$ → sales performance$_{t = 6 \text{ to } 7}$	H_{2a} (+)	5.98 (2.25)**	Supported
Commitment velocity$_{t = 1 \text{ to } 4}$ → sales performance$_{t = 4 \text{ to } 5}$	H_{2b} (+)	18.10 (10.90)*	Supported
Commitment velocity$_{t = 4 \text{ to } 6}$ → sales performance$_{t = 6 \text{ to } 7}$	H_{2b} (+)	28.77 (15.21)*	Supported
Controls			
Competitive distance → commitment velocity$_{t = 1 \text{ to } 4}$	N.A.	−.01 (.00)*	N.A.
Competitive distance → commitment velocity$_{t = 4 \text{ to } 6}$	N.A.	.00 (.00)	N.A.
Competitive distance → sales performance$_{t = 4 \text{ to } 5}$	N.A.	.01 (.02)	N.A.
Competitive distance → sales performance$_{t = 6 \text{ to } 7}$	N.A.	−.10 (.03)**	N.A.
Customer size → commitment velocity$_{t = 1 \text{ to } 4}$	N.A.	.01 (.02)	N.A.
Customer size → commitment velocity$_{t = 4 \text{ to } 6}$	N.A.	−.13 (.03)**	N.A.
Customer size → sales performance$_{t = 4 \text{ to } 5}$	N.A.	−.34 (1.11)	N.A.
Customer size → sales performance$_{t = 6 \text{ to } 7}$	N.A.	1.66 (1.64)	N.A.
R^2 commitment velocity$_{t = 1 \text{ to } 4}$		.06	
R^2 commitment velocity$_{t = 4 \text{ to } 6}$		.33	
R^2 sales performance$_{t = 4 \text{ to } 5}$		.04	
R^2 sales performance$_{t = 6 \text{ to } 7}$		.30	

*p < .05.
**p < .01.
Notes: N.A. = not applicable.

the presence (or absence) of a common developmental trajectory for relationship commitment, as well as the effect of commitment velocity on sales performance; in Study 2, we use a traditional approach to investigate the multiple moderated antecedents to commitment velocity.

Study 2: Drivers of Commitment Velocity

Study 2 focuses on our second research question—What factors drive commitment velocity, and how do these effects vary as the relationship develops or across different environments? This study has three specific objectives. First, we introduce an alternative measure of commitment velocity and show that it taps into the same underlying construct, in that we test its effect on sales performance (i.e., replicating our Study 1 findings). Second, we propose and test multiple drivers of commitment velocity to offer insights into which strategies are most effective for growing relationships. Third, we investigate how the effectiveness of the antecedents of velocity varies as a relationship matures (in years and stages) and across different contexts.

Specifically, in Study 2, we directly measure commitment velocity with a new multi-item scale that helps overcome some limitations of LGCM. In addition, by situating commitment velocity within a larger conceptual framework of key antecedents and outcomes, we increase our confidence in the nomological validity of the model. We test the expanded model with triadic data from a new business-to-business sample of matched customer and salespeople surveys and seller-provided sales performance data. The features in Study 2 also increase the generalizability of our findings (e.g., different samples, multiple selling firms, larger range of relationship ages, direct measure of velocity).

Identifying Drivers of Commitment Velocity

Most extant marketing research examines antecedents of commitment levels (Palmatier et al. 2006). In contrast, we study antecedents that drive the dynamic construct of commitment velocity. Increasing velocity requires that an antecedent do more than just provide a one-time lift in commitment (level); rather, it must enhance the ability of the relationship to grow. Thus, we adopt a dynamic capabilities lens (Teece, Pisano, and Shuen 1997) to investigate the antecedents of velocity. This theoretical perspective posits that the dynamic capabilities formed within an exchange are critical components for sustaining sales growth over time by increasing the intrinsic "ability" of an exchange to grow (Dyer and Singh 1998; Morgan and Slotegraaf 2012).

For example, a single investment may increase a partner's level of commitment from 4.0 to 4.1 (Likert scale), where it then remains constant (velocity = 0). In contrast, increasing exchange partners' *abilities* to make investments is probably more relevant for sustaining relationship growth (velocity) than one-time investments would be, because the exchange can better exploit opportunities that emerge through more effective investments now and in the future (Ulaga and Eggert 2006). Interfirm dynamic capabilities also are likely bilateral, in that they "depend on both parties' willingness to cooperate in joint learning activities" (Selnes and Sallis 2003, p. 80).

Extant research also suggests two general types of interfirm dynamic capabilities that appear critical to sustainable relationship growth (Dyer and Singh 1998; Palmatier, Dant, and Grewal 2007). First, partners must communicate effectively to identify new opportunities for joint value creation, which then support relationship growth. We include bilateral communication capabilities, or the ability of exchange partners to share information, as an antecedent of commitment velocity. For example, bilateral communication capabilities should be higher in relationships in which it is easier to share information and communication processes are well established. Second, exchange partners must be able to invest to exploit identified opportunities. We thus include bilateral investment capabilities, or the ability of relationship partners to make investments in their exchange, as an antecedent of velocity. Such bilateral investment capabilities should be higher in relationships between partners that are open to making investments in joint projects and know how to get each other to invest.[3]

In addition to critical capabilities, mechanisms must be in place to govern the shared risks and rewards of the relationship, which then allow partners to achieve their desired market positions (Ghosh and John 1999). Thus, we include *trust*, or confidence in a partner's reliability and integrity, as a governance mechanism that affects commitment velocity. Selnes and Sallis (2003) argue that trust facilitates ongoing learning and adaptation within an exchange relationship, with enduring effects on relationship performance.

To investigate the dynamic link between trust and commitment, we include relationship age as a moderating variable. In addition, we expect that the capabilities that a young relationship needs to begin growing will differ from those that a mature relationship needs to maintain growth; therefore, relationship age is a moderator of bilateral communication and investment capabilities. Dwyer, Schurr, and Oh (1987) similarly argue that exchange partners first must gain trust and engage in bilateral communication to explore opportunities for mutual growth and then invest to continue to expand their relationship. Furthermore, consistent with dynamic capabilities theory (Teece, Pisano, and Shuen 1997), we examine the moderating role of industry turbulence, or the degree of volatility and uncertainty in an industry, because "the effect of relational drivers may depend on external conditions; environmental uncertainty is the most critical contextual factor" (Palmatier, Dant, and Grewal 2007, p. 173).

To account for unmeasured (e.g., nonrelational) factors that might drive velocity and sales performance, with or without a strong relationship, we include two control variables that tap the nonrelational attractiveness of the partner to each respondent. Because a relationship may

[3]Communication and investments capabilities mirror the two key axes of March's (1991) classic framework of the perpetual learning required for organizations to adapt to changing conditions and maintain growth. In short, exploration (communication) and exploitation (investment) are critical for sustainable long-term growth (March 1991).

grow if a seller's product is stronger than alternative products (i.e., it has brand or performance factors that better help a customer achieve a desired competitive position; Ghosh and John 1999), we assess a customer's perception of the seller's product strength, relative to alternative products from competitors. Similarly, because customers that represent higher (vs. lower) levels of future sales opportunities will be attractive targets for incremental selling effort, all else being equal, we measure the seller's perception of the perceived opportunity offered by a specific customer. Figure 2 outlines our conceptual model for Study 2.

Effect of Customer Trust on Commitment Velocity

We expect trust to affect commitment velocity positively. Trust is an important antecedent of the growth of a relationship because it creates an environment in which learning and adaptation can take place (Dyer and Singh 1998; Selnes and Sallis 2003). As new opportunities for combining or creating resources arise, trust increases a partner's willingness to take risks (Morgan and Hunt 1994; Palmatier et al. 2006).

However, this effect is not without limits; over time, as a relationship matures, the positive linkage between trust and commitment velocity may diminish. Although trust is critical, it may not be sufficient for relationships to continue to grow. Exchange partners likely are especially diligent in evaluating their partners early in a relationship, which makes trust critical to the initial exploration and exploitation efforts that are necessary for a relationship to grow and progress to later expansion stages (Dwyer, Schurr, and Oh 1987). Trust also reduces social uncertainty, so that the customer is willing to take risks and incur vulnerabilities to commit to a relationship with the seller. A customer's acceptance of these risks enables the supplier to adapt its offerings and exploit opportunities that create value for the customer. However, as the relationship ages, trust may become less important because interactions grow routine, norms develop, perceived risk decreases, and fewer new opportunities are available. Even if a supplier is trustworthy over many years, a customer may shift attention to a competitor that offers new opportunities for value creation, causing the former relationship, despite high trust, to flatten and ultimately decay. Thus, although trust is still necessary, it is less important for maintaining or growing a relationship that has matured (Poppo, Zhou, and Ryu 2008). This prediction is consistent with research that shows a diminishing effect of trust over time (Hibbard et al. 2001).

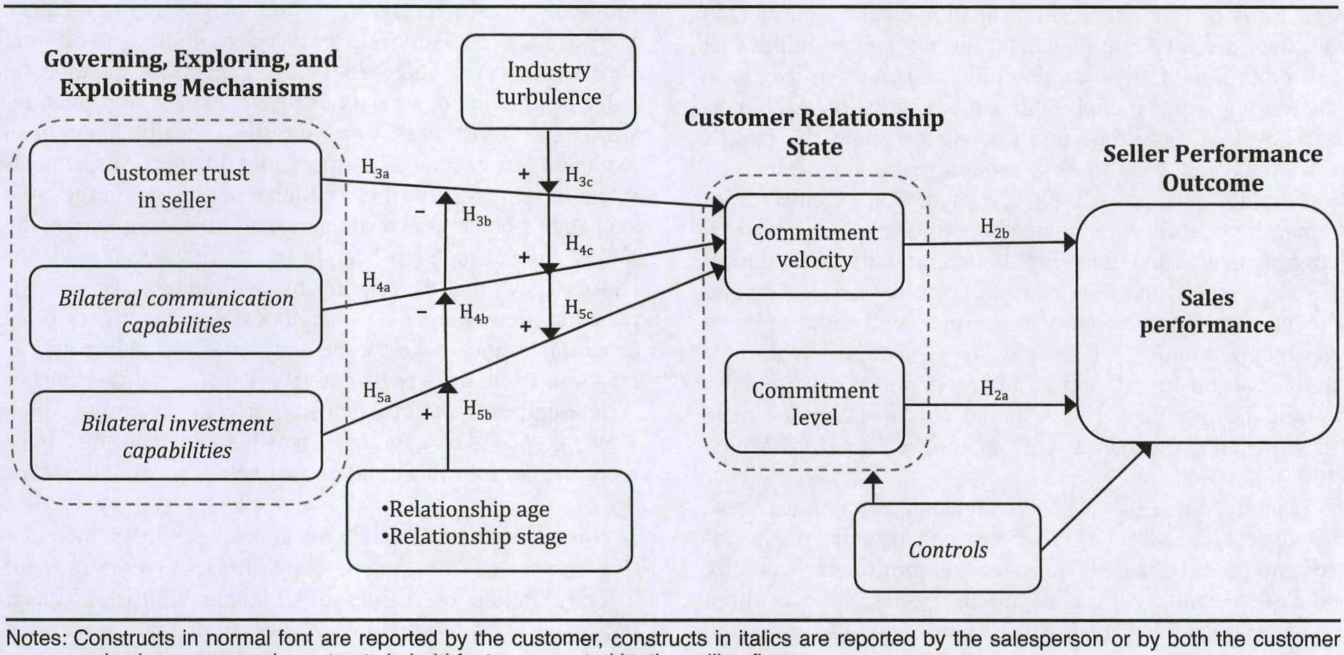
In addition, the impact of trust on commitment velocity should be stronger when industry turbulence is high. It is costly and time-consuming to rewrite contracts and monitor contractual performance in the face of dynamic market conditions, but trust allows exchange partners to adapt quickly, efficiently, and "on the fly" (Dyer and Singh 1998). Such trust-enabled nimbleness enhances the exchange relationship's ability to find and exploit growth opportunities in rapidly changing environments.

H_3: (a) Customer trust in the seller positively affects commitment velocity, but the positive effect (b) decreases as relationships age and (c) increases with greater industry turbulence.

Effect of Bilateral Communication and Investment Capabilities on Commitment Velocity

Communication between partners positively affects relationships by revealing points of similarity, resolving problems, providing a means to discover and align goals, and finding opportunities to create value by enhancing a customer's revenues or reducing its costs (Jap and Anderson 2007; Mohr, Fisher, and Nevin 1996; Selnes and Sallis

FIGURE 2
Study 2: Drivers of Commitment Velocity



Notes: Constructs in normal font are reported by the customer, constructs in italics are reported by the salesperson or by both the customer and salesperson, and constructs in bold font are reported by the selling firm.

2003). Communication capabilities among partner firms are critical because the complexity of value creation necessitates constant adaptation; value creation problems may be ill-structured and have unclear goals that evolve, include elements that are unknown, and produce results that are difficult to interpret (Aarikka-Stenroos and Jaakkola 2012). Ulaga and Eggert's (2006) study of customer value creation in business relationships uncovers a critical role of effective communication between partners. The accumulated knowledge and established information exchange processes that result from effective interactions allow partners to be responsive to changing conditions, such that suppliers can continue to create new value for customers and, over time, contribute to relationship growth. Specifically, through partners' mutual capabilities to exchange information, they can create value in the customer's "sourcing processes" by responding to changing requirements quickly, shifting responsibility for particular customer activities, improving problem solving, better aligning goals, and reducing inventory carrying and monitoring costs (Ulaga and Eggert 2006). Mutual communication capabilities also allow the customer to leverage the supplier's know-how to improve existing products and develop new products; effective communications produce the results in timely and cost-efficient ways (Ulaga and Eggert 2006).

Following this logic, bilateral communication capability positively affects commitment velocity because as conditions change (e.g., competitive actions), exchanges that are better at sharing information are more adaptable, so they can better avoid conflict and identify new opportunities, which is critical to sustaining and/or increasing a relationship's positive growth rate. Alternatively, an inability to communicate causes the relationship to stagnate, problems to fester, and partners to miss opportunities. We expect bilateral communication capabilities to have a positive effect on commitment velocity.

We also expect the impact of communication capabilities on commitment velocity to diminish as relationships age. Early on, communication capabilities allow partners to discover potential complementarities and opportunities that can be exploited, thus creating growth. However, over time and through regular exploration and exploitation, each partner develops rich, thorough knowledge about the other's resources and capabilities, reducing the importance of information sharing. Although communication capabilities remain critical for their adaptations to internal and external contingencies, and thus for maintaining the relationship (Mohr, Fisher, and Nevin 1996; Noordewier, John, and Nevin 1990), at some point, the partners will have exploited most opportunities for new avenues of value creation in their relationship. Because fewer opportunities remain, communication capabilities should be less likely to create incremental growth in a more mature relationship (March 1991).

Finally, consistent with our dynamic capabilities view, we expect industry turbulence to enhance the impact of communication capabilities on commitment velocity because operating in a turbulent industry places high demands on partners' ability to adapt to changing conditions, such that the importance of communication capabilities is greater (Fang, Palmatier, and Steenkamp 2008). Because accurate, timely knowledge is required to coordinate action effectively (Dyer and Singh 1998; Johnson, Sohi, and Grewal 2004), communication capabilities should be more important in turbulent industries. We expect the positive impact of communication on velocity to be stronger in turbulent industries because the impact of the bilateral ability to communicate to resolve problems and find new opportunities increases in a changing environment.

> H_4: (a) Bilateral communication capability positively affects commitment velocity, but the positive effect (b) decreases as relationships age and (c) increases with greater industry turbulence.

An investment in an exchange has a positive impact on interfirm relationships (Anderson and Weitz 1989; Ghosh and John 1999). However, to enhance velocity, rather than a one-time change in the commitment level, our dynamic perspective suggests the importance of factors that can enable the continued exploitation of new and diverse opportunities (March 1991). We focus on bilateral investment capabilities and argue that as exchange partners' ability to make investments in their relationship increases, the relationship can better exploit opportunities that emerge. Relationships that are open to investing and encourage mutual investments will be well positioned to continue to grow, currently and in the future. Specifically, investment capabilities result in the habitual exploitation of new opportunities to create exchange-specific assets, improve exchange efficiency, and refresh and expand the relationship, which enhance commitment velocity (Dyer and Singh 1998; Johnson, Tellis, and MacInnis 2005).

Unlike trust and communication capabilities, we expect the positive impact of investment capabilities on velocity to increase as the exchange ages. Relationships typically begin by identifying and exploring simple opportunities (i.e., low-hanging fruit); these "easier" opportunities allow the partners to assess the new relationship and typically require minimal investments (Kang, Mahoney, and Tan 2009). Until a deeper relationship is in place, unused investment capabilities offer little benefit for generating incremental value or growing new relationships. However, as a relationship ages, most easy opportunities already have been exploited, so exchange partners turn to more investment-intensive opportunities, which better leverage the exchange's bilateral investment capabilities. In addition, the longer an exchange has been in place, the more confidence partners have that the relationship will endure. These partners thus are willing, over time, to leverage their investment capabilities and make larger and time-consuming investments in exchange-specific assets, which produces greater "relational rents" and relationship growth (Dyer and Singh 1998, p. 664). In essence, investment capabilities have more impact on value creation and velocity as relationships age.

Finally, similar to communication capabilities, the positive impact of investment capabilities on commitment velocity should be greater in turbulent industries (Fang, Palmatier, and Steenkamp 2008). Exchanges that face changing technologies, customer preferences, and competitor positions also encounter more and greater opportunities for investment and should receive higher returns on their investment capabilities, which leads to relationship growth. Alternatively, enhanced investment capabilities offer few marginal benefits in a stable industry, because most opportunities already have been exploited.

> H_5: (a) Bilateral investment capability positively affects commitment velocity, but the positive effect increases (b) as relationships age and (c) with greater industry turbulence.

Sample and Data Collection

The data for Study 2 come from business customers, salespeople, and selling firms across high-technology, materials, and industrial product industries. Using multiple data sources reduces same-source bias concerns and enables us to collect measures from the most knowledgeable sources. Firms received a free benchmark report in return for their participation; each firm provided the e-mail addresses of a random, stratified sample of customers and their corresponding salespeople. We used a multiwave online survey in which the firms first sent an e-mail informing customers that they were involved in a joint industry–academic study sponsored by the Marketing Science Institute. The next day, we e-mailed the online survey to the customers, with an e-mail reminder one week later. For customers that responded (in addition to some that did not, to check for nonresponse bias), we sent a survey to "their salesperson," according to the same process, and asked the salesperson to answer questions about those customers. Finally, each seller provided objective sales performance data for each customer.

After removing cases (27) with either missing data or informants who indicated low knowledge levels (2 or less on seven-point scale), we obtained 380 different customer responses (9% effective response rate), matched to customer-specific salesperson responses provided by 137 different salespeople (72% response rate) from nine organizations. We used multiple tests to assess response bias. First, we compared early and late responses for all study variables. Second, we compared respondents who had been excluded from the final sample because of missing data with those whom we included across all study variables. No comparisons were significant ($p > .05$). We used data from three sources, and most of our hypotheses involved interactions or pertained to main effects measured with data from different sources, which minimizes any common method bias concerns.

Measures

We adapted existing measures whenever possible. All measures used a seven-point Likert scale, unless otherwise noted (see the Appendix). In measuring commitment level and velocity, we used three items each to assess commitment to the relationship at one point in time (i.e., level) and the direction and rate of change of the relationship (i.e., velocity). Specifically, we took care to ensure that no "level" items asked the informant to report on future expectations, which would imply some aspect of velocity. Many extant scales instead mix level and trend (i.e., future-oriented) items in the same scale, which confounds the static and dynamic components.

Sales performance was reported by the selling firm. Due to confidentiality concerns and some variation in performance metrics, we asked each firm to report its customer's sales performance on a ten-point scale (i.e., the top 10% customers based on annual sales growth received a score of 10). Most firms used annual sales growth (as in Study 1), but in some cases, firms indicated that performance-to-plan at a customer was a better representation of sales performance than year-to-year sales growth based on customer-specific factors (e.g., ending a large project).[4]

For each bilateral capability (communication and investments), we combined two items reported by the customer and two parallel items reported by the salesperson into a four-item scale that reflects a bilateral perspective. This approach reduces biases that may exist if we relied on a single source's perspective. The customer informants reported relationship age in years.

As control variables, seller's product strength, as reported by the customer on two items, captured the strength of the selling firm's product and service offering. We measured seller perceived opportunity with a single item, as reported by the salesperson, that captured the size of the potential opportunity for future sales offered by a specific customer.

We estimated a confirmatory factor measurement model, including all multi-item constructs. The fit indexes were acceptable: $\chi^2_{(114)} = 331.10$ ($p < .01$), CFI = .94, IFI = .94, and RMSEA = .06. The coefficient alphas of the latent constructs were greater than .70, which indicated internal reliability. Finally, we confirmed discriminant validity by verifying that the average variance extracted by each latent construct was greater than its shared variance with other constructs. We provide the descriptive statistics and correlations for all Study 2 constructs in Table 5.

Analysis and Results

To analyze the Study 2 data, we employ hierarchical linear modeling, which overcomes the limitations of traditional methods of analyzing nested data. We estimated a series of models using hierarchical linear modeling, in an empirical Bayesian procedure, with restricted maximum likelihood estimation. We mean-centered all variables to ease interpretation. The variance inflation factor was less than 3.0 in all models. Table 6 presents the results of our tests.

To evaluate the effects of commitment level and velocity on sales performance while accounting for the nested structure of our data, we included random intercepts at the salesperson and firm levels. Although we tested H_2 in Study 1, as a replication and extension, we retest this hypothesis with a direct measure of velocity. Commitment level did not significantly affect sales growth (Model 1: $\beta = -.10$, n.s.), so we reject H_{2a}. Commitment velocity positively influ-

[4]In 74 cases, firms reported sales performance using a ten-point scale based on customer's performance-to-plan. As a robustness test, we estimated Model 1 by dropping these cases to determine whether the different operationalization of sales performance influenced the results. The results remained consistent, increasing confidence in our measure.

TABLE 5
Study 2: Descriptive Statistics and Correlations

Constructs	M	SD	AVE	1	2	3	4	5	6	7	8	9
1. Commitment velocity	5.30	1.29	.55	.79								
2. Commitment	5.20	1.24	.52	.65**	.75							
3. Sales performance	5.77	2.63	N.A.	.11*	.10	N.A.						
4. Customer trust in seller	5.79	1.22	.72	.56**	.54**	.07	.84					
5. Relationship age	5.74	5.37	N.A.	.07	.20**	.02	.05	N.A.				
6. Bilateral communication capabilities	5.28	1.02	.54	.43**	.51**	.28**	.37**	.23**	.78			
7. Bilateral investment capabilities	5.01	1.01	.51	.42**	.46**	.12*	.32**	.11*	.51**	.79		
8. Industry turbulence	4.02	1.83	N.A.	–.03	–.02	.00	.02	.12*	.10	.07	N.A.	
9. Seller's product strength	5.27	1.26	.59	.48**	.55**	.07	.47**	.18**	.33**	.21**	–.00	.73
10. Seller's perceived opportunity	5.39	1.47	N.A.	.03	.15**	.33**	–.04	.12*	.44**	.28**	.07	.01

*$p < .05$.
**$p < .01$.
Notes: Coefficient alpha is reported on the diagonal. AVE = average variance extracted. N.A. = nonapplicable items.

enced sales performance (Model 1: $\beta = .26, p < .05$), in support of H_{2b}.

Next, we tested the influence of antecedents on commitment velocity by evaluating the direct effects of all hypothesized antecedents and control variables on commitment velocity (Model 2; Table 6). In Model 3, we added the six hypothesized interactions to Model 2; all three antecedents had significant direct effects on commitment velocity, such that customer trust (Model 3: $\beta = .34, p < .01$), bilateral communication capabilities (Model 3: $\beta = .24, p < .01$), and bilateral investment capabilities (Model 3: $\beta = .22, p < .01$) enhanced commitment velocity, in support of H_{3a}, H_{4a}, and H_{5a}, respectively. As we hypothesized, as the relationship aged, the positive effects of trust (Model 3: $\beta = -.03, p < .01$) and communication (Model 3: $\beta = -.02, p < .05$) on velocity diminished, in support of H_{3b} and H_{4b}. Alternatively, the positive effect of investment (Model 3: $\beta = .03, p < .01$) on commitment velocity increased, in support of H_{5b}. Of the three moderation hypotheses, only the positive interaction between communication and industry turbulence was significant (Model 3: $\beta = .07, p < .01$), in support of H_{4c}. Because the interactions between trust and industry turbulence and investment and industry turbulence were not significant, neither H_{3c} nor H_{5c} received support.

Post Hoc Comparison of Relationship Age and Life Cycle Perspectives

As a robustness check and to compare the relationship age and life cycle perspectives, we substituted life cycle stage for relationship age in Models 2 and 3 and report the results in Models 4 and 5 (see Table 6). Specifically, each customer selected one of four life cycle stages to best describe its relationship with the seller (see the Appendix). Both the first (exploration) and last (decline) stage captured relatively small portions (<9%) of the sample, so we combined the first two stages (exploration/expanding, coded as 0; 34% of sample) and the last two stages (maturity/decline, coded as 1; 66% of sample) to estimate Models 4 and 5. The results were consistent between age and life cycle perspectives, except that H_{5a}, which received support using age, was not supported when we used stages. These results suggest that age (continuous measure) and early versus late life cycle stages (dichotomous measure) captured similar developmental information; this finding adds to our confidence in the robustness of the moderation effects for trust, communication, and investment on commitment velocity.

Discussion

Most scholars agree that relationships fundamentally change over time, and yet most research in marketing promotes a static conceptualization, describing a customer's "relationship state" with a snapshot of the level of relational constructs (Morgan and Hunt 1994; Palmatier et al. 2006). This research adds a dynamic component, commitment velocity, to capture dynamic trend information that may be relevant to future exchange performance. In Study 1, by modeling six years of longitudinal data using LGCM, we confirm that commitment velocity is an empirically meaningful construct with a strong impact on sales growth, beyond static measures of level. In Study 2, by directly measuring commitment velocity in a new multifirm sample, we test a conceptual model of the antecedents and consequences of commitment velocity. We structure our discussion around the two research questions we outlined at the beginning of the article.

Role of Commitment Velocity in Relationship Dynamics and in Predicting Sales Performance

We find empirical support for the previously untested assumption of all three dynamic relationship perspectives (stage, age, velocity) that relationships in similar environments follow a common growth trajectory (vs. a unique or random walk). Specifically, we isolate and verify the significance of the underlying latent growth construct of commitment velocity, which helped explain the development of the relationships in our sample.

Furthermore, commitment velocity—or the rate and direction of change in relationship commitment—is a strong leading indicator of future sales growth. When commitment level and velocity are both included in the model, commitment velocity has a significant effect on sales

TABLE 6

Study 2 Results: Drivers of Commitment Velocity

Variable	Hypothesis (Directions)	Sales Performance	Commitment Velocity (Using Relationship Age)		Commitment Velocity (Using Relationship Stage)	
		Model 1	Model 2	Model 3	Model 4	Model 5
Effect of Commitment Level and Velocity on Sales Performance						
Commitment	H_{2a} (+)	–.10 (.14)				
Commitment velocity	H_{2b} (+)	.26 (.12)*				
Effects of Relationship Governing, Exploring, and Exploiting Mechanisms on Commitment Velocity						
Customer's trust in seller	H_{3a} (+)		.32 (.05)**	.34 (.05)**	.33 (.05)**	.47 (.09)**
Bilateral communication capabilities	H_{4a} (+)		.25 (.07)**	.24 (.06)**	.26 (.06)**	.41 (.10)**
Bilateral investment capabilities	H_{5a} (+)		.27 (.06)**	.22 (.06)**	.24 (.06)**	.08 (.10)
Relationship age/stage	N.A.		–.01 (.01)	–.01 (.01)	–.41 (.10)**	–.43 (.10)**
Industry turbulence	N.A.		–.04 (.03)	–.05 (.03)	–.04 (.03)	–.04 (.03)
Moderating Effects of Relationship Age, Relationship Stage, and Industry Turbulence						
Customer's trust in seller × relationship age/stage	H_{3b} (–)			–.03 (.01)**		–.21 (.10)*
Bilateral communication capabilities × relationship age/stage	H_{4b} (–)			–.02 (.01)*		–.22 (.12)*
Bilateral investment capabilities × relationship age/stage	H_{5b} (+)			.03 (.01)**		.25 (.12)*
Customer's trust in seller × industry turbulence	H_{3c} (+)			–.02 (.02)		–.04 (.03)
Bilateral communication capabilities × industry turbulence	H_{4c} (+)			.07 (.02)**		.08 (.03)**
Bilateral investment capabilities × industry turbulence	H_{5c} (+)			.01 (.03)		.01 (.03)
Controls						
Seller's product strength	N.A.	.07 (.12)	.27 (.05)**	.23 (.06)**	.25 (.05)**	.21 (.05)**
Seller's perceived opportunity	N.A.	.65 (.09)**	–.10 (.04)*	–.09 (.04)*	–.08 (.04)*	–.09 (.04)*
Deviance (–2 log-likelihood)		1725.29	1036.74	1001.74	1022.23	997.62
Proportion of variance explained		13.53%	45.97%	51.67%	47.22%	51.18%

*$p < .05$.
**$p < .01$.
Notes: The table reports parameter estimates with standard errors in parentheses. N.A. = not applicable.

growth in both studies and during relationship growth (Study 1; t_1–t_4) and decline (Study 1; t_4–t_6) stages. When we added commitment velocity to the model, the effect of commitment level on sales performance often became insignificant; thus, velocity may provide more performance-relevant information than level (as is typically measured in extant research). The superior performance-predicting ability of velocity over level may be due to the lack of valence or directional information contained in level. For example, as Figure 1 illustrates, relationships may display the same level of commitment at two points in time (dotted line), one with positive and one with negative velocity. A level-only perspective would predict that customers make similar choices at both points on the curve; conversely, accounting for commitment velocity provides additional behavior-relevant information, because customers' decision heuristics depend on their perceptions of the direction and rate of change in the relationship. Our findings align with theory that suggests that people tend to make decisions according to trends and are sensitive to change in relationships (Aronson 1969; Johnson, Tellis, and MacInnis 2005).

Our studies also provide a theoretical explanation for Jap and Anderson's (2007, p. 271) finding that "for the most part, maturity is never better than build-up and is often marginally inferior," because velocity is lower during the maturity stage, whereas a level-based perspective would predict opposite results. We also offer insight into Reinartz and Kumar's (2000) finding that age is not necessarily related to better performance. Consistent with their advice, we suggest that relationship duration does not offer a good proxy for relationship strength, because an older relationship could have peaked, in which case its flat or negative trajectory degrades performance. Managers should recognize the strong impact of commitment velocity, beyond level, on performance. Long-term relationships should be screened for stagnation, with appropriate efforts taken to restore growth (e.g., rotate salespeople, launch new products).

Drivers of Commitment Velocity: Moderating Roles of Age and Industry Turbulence

We have proposed that to predict the growth (i.e., velocity) versus level of a relationship, it is important to focus on the dynamic capabilities that enable members of a relationship to explore and exploit new opportunities over time (March 1991). Both bilateral communication and investment capabilities have positive effects on commitment velocity; trust, as a governance mechanism that enables continued adaptation, also relates positively to velocity. However, the positive impacts of trust and communication capabilities decline as a relationship ages. In other words, although trust and the ability to share knowledge effectively are critical for growth early in a relationship, at some point, their capacity to drive further growth diminishes. Bilateral investment capabilities instead relate even more strongly to velocity as a relationship ages.

Our results show that the impact of communication capabilities on commitment velocity increases for relationships embedded in turbulent environments. Because operating in a turbulent industry places high demands on a partnership's ability to adapt to changing conditions, it increases the importance of communication capabilities. Managers should recognize these dynamic effects and focus on building trust and communication capabilities (e.g., setting clear communication processes, making it easy to share information) early in the relationship. As the relationship develops, they can shift their efforts toward building bilateral investment capabilities by conveying openness to investing and ensuring their partners know the process for requesting such investments. In turbulent environments, extra efforts to build good communication capabilities should pay off for the firm.

Toward a Theory of Relationship Dynamics

In recent decades, two important streams of relationship research have generated a strong foundation of knowledge. One stream assigns a key mediating role to commitment (and its antecedent, trust) for capturing the relational content of an exchange and driving outcomes (e.g., Morgan and Hunt 1994; Palmatier, Dant, and Grewal 2007). The other stresses the developmental, path-dependent nature of relationships (see Table 1), such that the links among antecedents, relational variables, and outcomes depend on the relationship's life cycle stage or age (Dwyer, Schurr, and Oh 1987; Jap and Anderson 2007). We take a step toward unifying these streams by developing theory that uses commitment velocity to capture the dynamic aspect of commitment and to indicate an exchange's position along the relationship life cycle. Building on extant research, we offer three tenets to advance a theory of relationship dynamics that may help integrate the two streams into a unified framework.

First, the results of our two studies show that commitment velocity is often a stronger predictor of sales performance than commitment level, possibly due to the propensity to use trend extrapolation as a relational decision heuristic (Johnson, Tellis, and MacInnis 2005; Koriat, Fiedler, and Bjork 2006). Extant relationship marketing theory should be modified to incorporate the dynamic element of commitment (Morgan and Hunt 1994; Palmatier, Dant, and Grewal 2007) and other relational constructs to better capture relationship state (description of the precise condition of a relationship at a specific point time). Absolute levels are clearly important, but failing to account for the developmental, path-dependent nature of relationships may omit important performance-relevant information, which can produce misleading results and lead to faulty managerial implications. Therefore, as a first tenet of the theory of relationship dynamics, we postulate the following:

> Tenet 1: Both static and dynamic elements of relational constructs drive exchange performance, but dynamic elements are more critical than the static level for predicting future behaviors and performance.

Second, an important implication of our model, though not specifically tested, is that each relational construct develops according to the relative contributions of a unique set of underlying, time-varying processes. For example, commitment's growth trajectory results from the aggregation of various underlying processes, such as changes in interdependencies (dependence-based process) and evaluations of the benefits and costs of the relationship (value-based process). Each ongoing process can increase or decrease as the exchange develops, depending on circumstances; in aggregate, they determine the growth trajectory of the relationship.

As a post hoc test, we also estimated an LGCM for trust in Study 1 and found that trust, in contrast with commitment's inverted U shape, keeps increasing over the six-year period. Thus, trust appears to follow a positive linear trajectory, absent any trust-destroying event, that reflects the aggregate influences of different underlying processes than commitment, such as the accumulation of information about a partner's performance (learning-based cognitive process) or cycles of reciprocation (gratitude-based relational process). Both continuous processes are cumulative and should cause trust to increase over time, though perhaps at a diminishing rate.

The differences observed in the growth trajectories for commitment and trust, in this post hoc test using Study 1 data, differ from the results of most research, which proposes that relational variables develop together, growing and declining in parallel (Hibbard et al. 2001). For example, Jap and Anderson (2007, p. 262) note that "a multitude of relationship properties follow the same path, rising and falling tidily because many are related over time." A critical next step is to dynamically decompose the underlying processes of each relational variable, to isolate the antecedents and moderating factors influencing each unique growth process and, ultimately, to understand its developmental trajectory. This rationale leads us to a second tenet of the theory of relationship dynamics:

> Tenet 2: Relational constructs (e.g., trust, commitment, relational norms) follow unique path-dependent growth trajectories, according to the relative contribution of a construct-specific set of underlying time-varying processes.

Third, our empirical results and the preceding arguments suggest logically that if relational constructs have unique underlying processes that result in distinctive development trajectories, linkages among relational constructs likely vary over time as well. Previous cross-sectional studies that investigate linkages among latent relational constructs might capture just an "average effect" across a limited distribution of relationship trajectories (i.e., most exchanges in a sample tend to be in the maturity stage). Extending our results that showed that the positive effect of trust on commitment velocity is attenuated as relationships mature suggests that trust may be necessary, but it is not a sufficient condition for relationship growth. In other words, the large body of research proposing trust as a key antecedent of commitment may represent just the "effect size" for a relationship of average development or age. The effect of trust on commitment for younger or older relationships may vary markedly and be more complex than previously proposed.

For example, post hoc analyses dynamically linking the LGCM of trust and commitment show that the velocity of trust positively affects the velocity of commitment early in the relationship, but the constructs become decoupled as relationships mature. A dynamic linkage between trust and commitment parallels research on reading and math development processes, which tend to follow unique growth trajectories (due to their distinctive underlying developmental processes), such that the velocity of math ability often depends on the velocity of reading ability ("given the need for a child to accurately comprehend a written mathematics problem prior to solving it"; Bollen and Curran 2006, p. 191). Just as the rate of change in math ability depends on the level and rate of change in reading ability, the rate and direction of change in commitment appears to depend on the level and rate and direction of change in trust. Understanding how the static and dynamic linkages among relational constructs change as relationships evolve could help scholars identify the most effective acquisition and retention strategies and isolate how constructs change in relative importance as relationships develop. Thus, the third tenet of the theory of relationship dynamics we propose is as follows:

> Tenet 3: As relationships evolve, there are changes in (a) the linkages among relational constructs and (b) the relative importance of relational constructs for influencing exchange outcomes.

Limitations and Further Research

The use of two methods and multiple samples increases confidence in our results, though each approach has its weaknesses. Study 1 explores a portfolio of newly formed relationship dyads involving a single company with multiple independent channel partners, which minimizes extraneous variance from multiple sellers. Although we do not believe that relationship development processes differ significantly for other firms, we cannot precisely discern the impact of the unique characteristics of this seller. Study 2 uses customer and salesperson surveys, matched with performance data, to minimize common method concerns, but the effect sizes between constructs from the same source may be inflated, and this design provides limited causal insight (Rindfleisch et al. 2008). A benefit of our two-method approach is that we demonstrate empirically that commitment velocity can be measured with a scale and does not need to be extracted from longitudinal data. Thus, scholars can incorporate the construct into studies, even if they cannot implement longitudinal designs or LGCMs. The survey items in Study 2 that measure commitment velocity capture a broader domain than the items used in Study 1; further research should investigate the optimal scope for measuring the velocity of different constructs (relationship quality, commitment, trust, norms, gratitude).

Finally, our studies focused on one governance mechanism (i.e., trust) and the variation in its impact as a relationship develops. To develop a theory of relationship dynamics more fully, additional research should investigate other mechanisms that may substitute for or complement trust and that have different dynamic properties (e.g., contracts, norms). Other research could apply the LGCM approach to alternative constructs (e.g., gratitude [Palmatier et al. 2009], satisfaction [Geyskens, Steenkamp, and Kumar 1999]) to provide a more complete picture of relationship dynamics.

For example, "emotion-based" gratitude might have a relatively short life, such that sellers can collect on feelings of gratitude for only a short time after an investment. In contrast, relational norms may take more time to develop but be more resistant to decay (displaying relational inertia). Researchers should assess the velocity of these other constructs, because if customers make decisions according to trends, then level-only measures will provide faulty guidance. For example, firms that label all customers beyond a prescribed level as "satisfied" may miss important trend information and make myopic decisions. Studies that indicate that the levels of customer satisfaction are poor predictors of future performance might yield alternative results if they were to take a dynamic perspective.

APPENDIX
Construct Measures

Constructs/Measures (Scale Sources)	Item Loadings
Study 1 Constructs	
Customer commitment (Kumar, Hibbard, and Stern 1994; customer reported)	
We continue to represent [Seller] because it is pleasant working with them.	.88
We intend to continue representing [Seller] because we feel like we are part of the [Seller] family.	.88
We like working for [Seller] and want to remain a [Seller] agent.	.73
Competitive distance (customer reported)	
Number of miles to nearest direct competitor.	N.A.
Customer size (customer reported)	
Number of employees at customer firm.	N.A.
Sales performance (seller reported)	
Annual sales growth calculated from sales revenue data.	N.A.
Study 2 Constructs	
Commitment velocity (developed for study; customer reported)	
Our relationship with this seller is improving.	.74
Our firm's relationship with this seller is getting worse over time. (reversed)	.62
Our relationship with this seller is on a positive trajectory.	.87
Commitment (adapted from Palmatier 2008; customer reported)	
We are willing "to go the extra mile" to work with this seller.	.63
We feel committed to our relationship with this seller.	.76
In aggregate, we have a high caliber relationship with this seller.	.71
Sales performance (seller reported)	
Annual sales growth performance data from seller's database.	N.A.
Customer trust in seller (Palmatier 2008; customer reported)	
We have trust in this seller.	.87
This seller is a trustworthy company.	.83
Relationship age (years) (customer reported)	
On average, how long have employees at your firm had relationships with this seller?	N.A.
Relationship stage (adapted from Jap and Ganesan 2000; customer chose one stage)	
Exploration stage: The relationship between my firm and this seller is just beginning to develop.	N.A.
Expanding stage: The relationship between my firm and this seller is expanding and growing stronger.	N.A.
Maturity stage: The relationship between my firm and this seller is mature and relatively stable.	N.A.
Declining stage: The relationship between my firm and this seller is starting to decline.	N.A.
Bilateral communication capabilities (adapted from Mohr, Fisher, and Nevin 1996)	
We have good communication processes in place with this customer. (salesperson reported)	.55
Sharing information between our firms is relatively easy. (salesperson reported)	.54
We have good communication processes in place with this seller. (customer reported)	.88
Sharing information between our firms is relatively easy. (customer reported)	.71
Bilateral investment capabilities (adapted from Palmatier, Dant, and Grewal 2007)	
Both of our firms are open to making investments to advance joint projects. (salesperson reported)	.67
Both of our firms understand how to get each other to invest in new opportunities. (salesperson reported)	.56
Both of our firms are open to making investments to advance joint projects. (customer reported)	.64
Both of our firms understand how to get each other to invest in new opportunities. (customer reported)	.66
Industry turbulence (adapted from Fang, Palmatier, and Steenkamp 2008; customer reported)	
The industry in which our firm operates is very volatile and uncertain.	N.A.
Seller's product strength (customer reported)	
The brands of the products/services your firm purchases from this seller are very strong.	.88
This seller's brands are stronger than most of its competitors.	.66
Seller's perceived opportunity (seller reported)	
This customer represents a large potential opportunity for my firm.	N.A.

Notes: Items in Study 1 (2) are measured using five-point (seven-point) scales anchored by 1 = "strongly disagree" and 5 (7) = "strongly agree," unless otherwise indicated. N.A. = not applicable.

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