Marketing Science Institute Working Paper Series 2019
Report No. 19-115

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February 9, 2019

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Customer onboarding is a dynamic process by which new customers have their first experiences with a firm's offerings and employees, leading to the formation of influential relationship foundations. Prior research investigates the processes of identifying and acquiring new customers (e.g., Stahl et al. 2012; Tillmanns et al. 2017), yet academic research into the unique role of a firm's relationship-building activities during the customer onboarding period and their resultant impact on performance is scarce (Voorhees et al. 2017).[1] This gap is surprising, considering the vast body of managerial studies of customer onboarding and the long history of organizational research highlighting the importance of onboarding for enhancing employees' commitment (e.g., Solinger et al. 2013) and performance (e.g., Bauer et al. 2007).

Practitioners recognize that onboarding "sets the tone for your ongoing relationship" with customers (Perricone 2018, p. 2) and further that "*communication* during the onboarding process will be what makes or breaks your relationship with your customer" (Laplante-Dube 2018, p. 11). Communication generally refers to the direct, often bilateral exchange of information between a firm or employee and a customer (Kozlenkova et al. 2017). The growth of multichannel communication (e.g., face-to-face, phone, email) adds another important consideration to customer onboarding strategies. Namely, the varying richness of different communication channels (e.g., number of visual and verbal cues) affect the capability of each channel to build relationships with customers (Walther and Parks 2002; Yadav and Varadarjan 2005). Accordingly, *we seek to understand and isolate the effect of customer onboarding on performance in a multichannel communication environment.*

[1] A November 2018 search in the EBSCO database for "onboarding" in marketing academic journals identified only one article, in strong contrast with a Google search for "customer onboarding white paper" that returns more than 100 managerial and consultant-oriented articles.

To do so, we leverage insights from two independent streams of research to propose a novel, conceptual framework. First, to capture the unique and inherently dynamic process of initial relationship formation, we adopt first impression (Leary and Kowalski 1990; Willis and Todorov 2006) and relationship marketing dynamics (Palmatier et al. 2013; Zhang et al 2016) theories. These theories suggest that initial communications and interactions have particular importance, because customers start to assess and form initial mental models or first impressions of their relational partners. These early communications are more influential (i.e., greater initial effect) and have longer-lasting effects (i.e., slower decay and stronger carryover effect) compared to the impact of similar communications later in the relationship. Second, to address the unique characteristics of different communication channels, we apply media richness (Daft and Lengel 1986; Walther and Parks 2002; Yadav and Varadarajan 2005) theories, which assert that richer channels transfer more meaning, resolve ambiguities, and speed up relational development more effectively than do leaner channels (e.g., face-to-face vs. email). However, richer channels also impose additional costs on both the firm (e.g., time, resources) and the customer (e.g., time, processing effort). Thus, we propose that richer communication channels are more effective during onboarding, when customers use all available information to build their initial mental models. Our conceptual model integrates first impression and relationship dynamics with media richness theories to explicate the dynamic effects of multichannel onboarding communication on performance.

We test the proposed multichannel communication model with data from a large *Fortune* 500 company that sells an array of financial products and services. The random sample consists of 201,398 retail banking customers, all of whom began their relationship with the firm in the same month, which is key for empirically isolating early relationship onboarding effects. With a longitudinal data collection, we track face-to-face, telephone, and email interactions over 20 months. The interactions are specific to marketing communications (e.g., relational communications, product pitches); we account for all other transactional and servicing interactions with control variables (e.g., using an ATM, cashing a check, making a deposit). The panel nature of our data set produces a final sample that consists of 3,122,546 monthly observations. The outcome variable is each customer's share of wallet (SOW) over the 20-month timeframe, allowing us to integrate competitive effects while also capturing the ceiling effects of sales to individual customers. Using a Bayesian approach, we estimate the simultaneous effects of multiple communication channels on SOW over time. To account for the potential endogeneity of each communication channel, we also use an instrumental variables approach (Lopes and Polson 2014). The results, with several supplementary analyses, provide three key theoretical and managerial contributions regarding onboarding in a multichannel communication environment.

First, *we theoretically and empirically decompose onboarding into two key mechanisms: encoding and carryover*. Communication in any channel has a significantly greater impact on performance during the customer's initial experiences with the firm, as a consequence of (1) paying more attention and processing early communication more while building initial mental models (encoding) and then (2) making decisions in the future by accessing these mental models, such that early model-building communication also affects actions in later periods (carryover). We define the *onboarding window,* or onboarding half-life, as a period of time that it takes for 50% of the onboarding communication benefits to dissipate (i.e., no longer available for firms to leverage) and it appears to last approximately four months; it takes a year for 90% of the total onboarding benefits to disappear. Furthermore, consistent with our theoretical predictions, the *encoding* mechanism dominates the overall effect of communication on performance (SOW) in early interactions, accounting for 58% of total effect for face-to-face (FTF) and 82% for email communications in the first month. Then the *carryover* mechanism surpasses encoding as the more important mechanism later, when customers use their previously encoded mental models to make decisions while ignoring or biasing against any inconsistent information received from later communication. This carryover effect decreases as time elapses. By identifying and decomposing customer onboarding mechanisms, this research shows for the first time that carryover effects are *time-varying* and provides empirical insights into the duration (window) and magnitude of customer onboarding. Without accounting for these factors, firms might underestimate and underinvest in communication during the onboarding window, as well as overestimate the effects of communication after this window.

Second, by investigating *customer onboarding in a multichannel communication environment, we capture the relative importance of richer versus leaner channels during onboarding,* which is not possible to observe with single- or aggregated-channel research. Consistent with richness theory, we find that the effects of communication on performance are greater for richer than for leaner channels. More compellingly, the results support arguments that the relative benefits of richer over leaner channels are significantly greater during the onboarding period than afterward, due to the impression-enhancing, relational-building cues (e.g., body language, tone of voice) available through richer channels. Richer communication channels appear especially critical when customers pay close attention and fully process communication to encode or build their initial mental models about a seller. This study is the first to show empirically that onboarding mechanisms significantly enhance the effects of richer versus leaner communication channels. For example, FTF communication has 19 times greater impact on performance in the first month than it does just two years later (post-onboarding window). The results specify the ways in which richer communication can better leverage onboarding benefits, leading to the recommendation that they should be used with greater frequency early in customer relationships.

Third, with a series of supplementary analyses, *we clarify some theoretical conflicts from extant multichannel communication research and identify several managerial strategies for effective customer onboarding*. For example, Reinartz, Thomas, and Kumar (2005) argue that interactions of FTF with email or telephone channels increase performance (positive interaction), but Godfrey, Seiders, and Voss (2011) find negative interactions across various pairs of communication channels. We reconcile these past conflicting results by demonstrating that all multichannel interaction effects switch from being complementary (positive interactions) to being substitutive (negative interactions) as time passes. A breakeven analysis by channel suggests that the tipping point differs somewhat across pairs: 4.5 months for FTF×telephone, 5.7 months for FTF×email, and 4.3 months for telephone×email interactions. Overall though, customer relationships that have existed for less than about five or six months will tend to exhibit positive interactions (multichannel complementarities), whereas relationships that are older may reveal negative interactions (multichannel substitutions) across different communication channels. We posit that communication channels exhibit positive interactions during the onboarding window because their complementary characteristics (e.g., visual cues in FTF, revisability in email) help new customers build stronger mental models through the attention and processing effort they devote to integrating the multichannel communication. Later in the relationship, after onboarding, customers instead are less motivated to expend the cognitive effort to integrate multichannel communication, because they already have a well-formed relational mental model and are more interested in narrowly addressing specific product or service issues. In this case, different channels mostly substitute for one another (negative interactions), and richer channels offer more information but at higher costs. Thus, complementarities among channels may be most valuable when customers are highly attentive and seek to build their initial impressions—that is, in the onboarding period.

Understanding Multichannel Customer Onboarding

Customer onboarding represents a critical first stage in the customer journey. Accenture, a leading global consulting firm, asserts that "getting the client onboarding experience right over the first 90 to 120 days of the relationship is essential. Performed properly, onboarding activities help set the foundation for a deeper, more profitable long-term relationship" (Weingarten 2018). An existing definition of customer onboarding as "the process of familiarizing a customer with a firm's service offering" (Voorhees et al. 2017, p. 274) restricts the focus to *learning* about a firm's products or services, so we expand the scope explicitly to recognize three key elements of customer onboarding: it is (1) a dynamic process, (2) relevant only for new customer experiences for a relatively short period for both offerings (products/services) and employees, and (3) critical for forming a foundation for the relationship's future trajectory. Therefore, we define *customer onboarding* as a dynamic process by which new customers have their first experiences with a firm's offerings and employees, leading to the formation of influential relationship foundations.

Onboarding activities primarily get delivered through communication; communication is essential for establishing relationship foundations, because it provides "the basis for the emergence of trust, continued interaction, and ultimately commitment" (Palmatier et al. 2013, p. 17). *Communication*, the direct, often bilateral exchange of information between a firm or employee and customer (Kozlenkova et al. 2017), rarely occurs through a single channel though; multiple channels are the norm, especially for new customers (Morris 2013). Communication channels vary in their level of richness and cost structures (Daft and Lengel 1986; Reinartz, Thomas, and Kumar 2005), as well as their relationship-building effectiveness (Walther and Parks 2002; Yadav and Varadarajan 2005), which should inform multichannel onboarding.

To account for these complexities, we review research on three extant theoretical perspectives relevant to customer onboarding, as detailed in Table 1. First, we rely on *multichannel communication research* as a basis for linking communication to performance. Second, we integrate *first impressions and relationship marketing theories* to capture the inherent relational dynamics associated with customer onboarding. Third, we connect *media richness and social information processing theories* to multichannel communication dynamics to account for the fundamental differences of various communication channels.

Multichannel Communication Research Perspective on Customer Onboarding

Research consistently shows that communication with customers, typically operationalized by its frequency, has a curvilinear relationship with firm performance (e.g., Kumar, Venkatesan, and Reinartz 2008; Venkatesan and Kumar 2004). An inverted U-shaped effect of communication on performance captures the tension between benefits and costs; at some point, the costs (time, effort, social) of additional communication outweigh any gains in improved understanding or relational bonding. This functional form appears consistent across different communication channels.

Communication research is less consistent with regard to the potential interactions among different communication channels (multichannel interactions). Reinartz, Thomas, and Kumar (2005) find that FTF and email channels, as well as telephone and email channels, synergistically increase performance (positive interactions), whereas another study reveals negative interactions (Godfrey, Seiders, and Voss 2011). A dynamic or onboarding perspective potentially provides insight into these inconsistencies. Overall, multichannel onboarding should capture two known effects of communication on performance, namely, the inverted U-shaped relationship and the interactions among communication channels (multichannel interactions). We incorporate and control for these known effects to allow us to specify and then to isolate the additional effect of customer onboarding.

First Impressions and Relationship Marketing Dynamic Perspective on Customer Onboarding

To understand how customer onboarding, an inherently dynamic process of initial relationship formation, affects the communication–performance link, we draw from first impressions (Leary and Kowalski 1990; Willis and Todorov 2006) and relationship marketing dynamics (Palmatier et al. 2013; Zhang et al 2016) theories. These research streams suggest the critical importance of early customer–employee/firm communication but anticipate that communication quickly becomes less impactful over time (Palmatier et al. 2013). During onboarding, customers assess and form their first impressions, or mental models, of the firm's offerings and employees, so communication is highly influential. First impressions are persistent and "relevant from a social perspective for future interactions, requiring that they be transferred to memory" (Gilron and Gutchess 2012, p. 85). In turn, first impressions are strong, difficult to overcome, and long lasting (Bitner 1995; Evans et al. 2000; Lim, Benbasat, and Ward 2000); they set the tone for the future relationship, in that they "provide the anchor from which subsequent judgments are realized" (Ambady, Bernieri, and Richeson 2000, p. 201). People therefore make biased evaluations of subsequent interactions *in light* of their first impressions. The relationship foundation that forms can be positive or negative but strongly influences the future relationship trajectory (Asch 1946; Lim, Benbasat, and Ward 2000). Accordingly, communication's effect on performance should be greatest at the start of the relationship and decrease relatively quickly after a customer forms an initial mental model, then applies this model to make future decisions. With these theoretical underpinnings, we propose that onboarding affects performance through two different mechanisms or pathways.

First, early communication should have an enhanced impact on performance in the time period during which it is *occurring,* which we refer to as ***onboarding encoding.*** Customers pay more careful attention to communication when building their initial mental model, such that they fully process all available cues and informational content. The enhanced attention and processing likely leverages the effect of early communication as customers encode the data to build their mental models. Second, early communication should have an enhanced impact on *future* performance (i.e., in future periods), which we term ***onboarding carryover.*** Customers use early encoded mental models to make decisions in the future, to evaluate future information to match their existing mental models, and may even ignore subsequent communication that is too inconsistent with their mental models. Thus, the use of existing mental models enhances the effects of prior communication on decisions in the future.

Media Richness and Social Information Processing Perspective on Customer Onboarding

A third perspective focuses on the fact that in today's world customer communication typically occurs through multiple channels (Hyken 2018). However, most research in marketing examines either a single communication channel (Sun and Li 2011) or aggregates communication measures across multiple channels (e.g., electronic, traditional mail, and fax aggregated into one measure in Cannon and Homburg 2001; aggregated telephone and mail in Venkatesan and Kumar 2004). Single- or aggregated- channel studies offer important insights but cannot support comparisons across multiple communication channels with regard to their differential roles in customer onboarding. Studies that investigate the unique effects of various channels indicate that richer communication channels typically have greater effects on performance than leaner channels (Godfrey, Seiders, and Voss 2011; Reinartz, Thomas, and Kumar 2005), but these studies do not consider dynamic or customer onboarding effects, which would require identifying and modeling all customer communication from the beginning of their relationship with the firm.

Building on empirical insights from multichannel studies, we adopt the theoretical lens of *media richness* and *Walther's (2008) social information processing theories* to account for the relative effectiveness of different channels for customer onboarding. Media richness theory asserts that communication channels differ in their levels of richness, reflecting "the ability of information to change understanding within a time interval" (Daft and Lengel 1986, p. 560). Richer channels can transfer complex information faster and with fewer misunderstandings than leaner channels, due to their capacity for immediate feedback (synchronicity), personal focus, multiple cues (e.g., verbal, visual), vocalisms (e.g., tone, pitch, articulation), and natural language, all of which foster mutual understanding. Walther's social information processing theory further emphasizes the dynamic effects and relational-building capabilities of richer communication channels, suggesting that rich channels provide *social information* (e.g., tone of voice, body language) that enhances first impressions and also *accelerates relational development* (Walther and Parks 2002; Walther et al. 2015).[2] Richer channels thus may enhance both onboarding mechanisms of encoding and carryover. Extant research ranks communication

[2] We use the term "richness" to refer collectively to both media richness theory and the extension in Walther's social information processing theory.

channels in order of decreasing richness as (1) FTF, (2) telephone, and (3) email (Daft and Lengel 1986; Reinartz, Thomas, and Kumar 2005).

Although rich channels are associated with greater informational and relational benefits, they entail higher *communication costs* due to the time, effort, and cognitive load required from message recipients (Berger 2014; Palmatier et al. 2008). For example, when communicating face-to-face, parties can see and hear one another but must be present in the same location at the same time. In contrast, an email channel prevents the parties from seeing or hearing one another but allows them to be in different places and respond at their convenience.

In summary, to understand multichannel customer onboarding we integrate insights from three perspectives. Multichannel communication research suggests that communication affects performance in an inverted U-shaped form, with varying interaction effects across different communication channel pairs. We also integrate first impressions and dynamic relationship marketing theories to identify the time-varying onboarding mechanisms of encoding and carryover and capture the dynamics associated with customer onboarding. Finally, we connect media richness and social information processing theories to multichannel communication dynamics to account for the fundamental differences of various communication channels as they pertain to onboarding and relationship formation.

Conceptual Model and Hypotheses

Our review of relevant research and theories reveals that to develop a conceptual model that captures the dynamic nature of customer onboarding in a multichannel environment, we must simultaneously account for the known communication effects, onboarding dynamic mechanisms, and onboarding richness effects. From a multichannel view, we investigate the three most popular business communication channels (Alton 2016): face-to-face, telephone, and email. We use customer share of wallet (SOW) as an outcome variable, because it is broad enough to capture multiple performance-enhancing aspects of communication (e.g., purchase, expansion, retention behaviors), competitive effects, and the natural ceiling effect of sales growth for individual customers in most contexts (Chen and Steckel 2012). Figure 1 provides a visual representation of our conceptual model.

Known Communication Effects

Our review of extant communication research reveals four known elements of the effect of communication on performance: an inverted U-shape, interactions among channels, current communication richness, and past communication richness. All four communication effects have been well documented in extant research, so we briefly discuss each one, include them in our conceptual model, and test for replication, without offering formal hypotheses.

Multichannel inverted U-shaped effect. At some point, additional communication in any channel should reduce performance, due to the inverted U-shaped effect. Godfrey, Seiders, and Voss (2011) show that after three telephone contacts, customers start to experience negative reactance, and their spending levels decrease. Initially though, communication helps, by fostering mutual understanding and relational bonds so that firms can understand customers' needs, and customers can learn about a firm. Such benefits help lessen customers' feelings of uncertainty and generate reciprocity, thereby increasing purchase likelihood (Kozlenkova et al. 2017). After a certain point, customers perceive each additional contact as more of a hassle, requiring too much time, energy, social effort, or cognitive burden relative to the small incremental benefit gained from the additional interaction. In other words, too much communication becomes counterproductive and can even push customers away (Fournier, Dobscha, and Mick 1998). In line with this reasoning, all communication channels should have an inverted U-shaped effect on performance.

Interactions between communication channels. Communication in one channel can either enhance or suppress the effect of communication in another channel on performance. According to one study, 74% of customers use at least three different channels to communicate with a firm for customer-related issues (Morris 2013). However, empirical evidence about whether the use of multiple channels helps or hurts performance is mixed. As we noted previously, Reinartz, Thomas, and Kumar (2005) find positive or complementary interactions between FTF and email channels, as well as between telephone and email channels, but Godfrey, Seiders, and Voss (2011) find negative or substitutive interactions for all these combinations. A complementary interaction should arise if the different characteristics of various communication channels provide unique benefits (e.g., visual cues, synchronicity). A substitutive interaction instead may occur if communicating with customers through different channels leads to additional integration costs and unnecessary redundancy, with few added benefits.

Current and past communication channel richness. Holding all else equal, richer channels should have greater effects on performance than leaner channels, in line with media richness theory and previous research (e.g., Kumar, Venkatesan, and Reinartz 2008; Reinartz, Thomas, and Kumar 2005). The effect of both the current period's communication and all past cumulative communication on performance should be greater for richer versus leaner channels. Richer channels typically have greater effects on performance, due to their ability to transfer complex information quickly and more accurately, enhance first impressions, and accelerate the relational trajectory (Daft and Lengel 1986; Walther and Parks 2002; Yadav and Varadarjan 2005). The FTF channel should have the greatest impact, followed by telephone and then email.

Face-to-face is the richest channel, because "it provides immediate feedback so that interpretation can be checked. Face-to-face also provides multiple cues via body language, physical gestures, and tone of voice, and message content is expressed in natural language" (Daft and Lengel 1986, p. 560). Although visual cues (e.g., body language, gestures, facial expressions) are absent from both telephone and email communication, telephone still provides immediate feedback, which keeps the conversation relevant, and verbal cues, such as tone, pausing, inflection, or rate of speech, that can signal levels of interest, knowledge, and cooperation. Our conceptual and empirical models include these known effects and predict that onboarding mechanisms are independent and additive, such that we attempt to isolate their unique effects on performance.

Onboarding Dynamic Effects

First impressions and relationship marketing dynamics theories collectively propose that communication's impact is greatest at the beginning of the relationship and then dissipates as the relationship ages (Palmatier et al. 2013; Willis and Todorov 2006). As prior research suggests, "relationships and interactions will be a lot easier if you're able to immediately start off strong" (Knight 2016, p. 2). During initial encounters, customers assess and form their first impressions, by building mental models of sellers' products, services, and employees, so communication will be highly impactful. Because customers are highly attentive and more likely to process all communication cues to build their initial mental models about the firm and its employees, the effects of this initial communication on beliefs (e.g., trustworthiness) and performance-related behaviors (e.g., repurchasing, cross-buying) should be greater than later on. Any communication early in a relationship is likely more focused on, attended to, and better remembered than the same communication occurring later (Lewis 2004; Lim, Benbasat, and Ward 2000). The initial mental models also are strong, difficult to overcome, and long lasting (Bitner 1995; Evans et al. 2000; Lim, Benbasat, and Ward 2000). Because these first impressions and mental models influence decision-making far into the future, the communication that informs the formation of these models likely has far-reaching, persistent effects (i.e., effects that carry over into the future). Communication thus should be more impactful early in the relationship, during the onboarding window, as customers build or encode mental models and then start to use those mental models.

Thus, communication early in the relationship should have an enhanced impact on performance as it is *occurring*, because customers pay more careful attention when building their initial mental model and processing all the cues and information content available. This "encoding" onboarding mechanism occurs during the mental model building stage, and the related *early communication lift is due to customers' enhanced attention and increased processing*. After they have built mental models, customers continue to access them to make decisions, such that these early models set the tone for the relationship and "provide the anchor" for future decisions (Ambady, Bernieri, and Richeson 2000, p. 201). Because they bias subsequent interactions, the effects of the initial communication carry over to future periods (Asch 1946; Lim, Benbasat, and Ward 2000), resulting in a second onboarding mechanism, such that communication has a greater impact on *future* performance because customers access initial mental models to make decisions, bias future information in light of those models, and ignore subsequent communication that is inconsistent with existing mental models. This "carryover" onboarding mechanism reflects the relatively greater influence of early period marketing on future period decisions; the *early communication lift exists because the initial model-building communication affects decisions in the future.* However, we expect these onboarding carryover effects to decrease over time, in contrast with previous marketing research that typically assumes carryover effects to remain constant (Köhler et al. 2017; Zantedeschi, Feit, and Bradlow 2016). Once an initial mental model exists, subsequent communication no longer offers the same benefits, because it does not inform model building. That is, onboarding carryover is a temporary mechanism (time-varying), unlike typical effects by which marketing (e.g., advertising) in one period carries over to the next period at the same rate (time-invariant or constant).

In summary, onboarding and the early relationship communication boost results from both encoding (greater impact of communication in the current period) and carryover (greater impact of present communication in future periods) mechanisms. These new customer communication benefits operate in conjunction with and additionally to other known communication effects.

H_1: Communication's effect on present-period performance is enhanced for new customers, such that it is greater initially and then quickly dissipates as a new relationship ages for (a) face-to-face, (b) phone, and (c) email channels (i.e., *onboarding encoding*).

H_2: Communication's period-to-period carryover effect on performance decreases as the relationship ages for (a) face-to-face, (b) phone, and (c) email channels (i.e., *onboarding carryover*).

Onboarding Richness Effects

Communication channels vary in their capability to transfer information, build first impressions, form relationships, and aid in information recall (Lim, Benbasat, and Ward 2000; Walther and Parks 2002). Drawing from media richness and social information processing theories, we argue that the benefits of richer communication channels should be reflected in stronger effects for richer versus leaner channels, across both onboarding mechanisms. Richness benefits should be especially critical in early onboarding periods when initial impressions form, relationships foundations develop, and mental models are more salient.

Specifically, the effect of onboarding encoding should be greater for richer versus leaner channels. During onboarding, customers need as much data as possible to form their initial impressions and familiarize themselves with the firm, employees, and offerings. In their attentive, encoding state, new customers also are more motivated to expend the effort to integrate and process multiple cues available in richer communication channels, which they might ignore later in the relationship, once they have gained sufficient familiarity. Richer channels speed up relationship development by providing additional information that would be unavailable through leaner channels such as email (Walther and Parks 2002; Walther et al. 2015). For example, FTF communication "is essential as a pre-condition to create familiarity and mutual coding schemas" (Torres-Coronas and Arias-Oliva 2009, p. 679). With richer channels, people gather cues such as vocal inflection and hand gestures to encode messages, then adapt their responses accordingly, which makes the initial contact more effective (Franke and Park 2006). Customers use visual cues (e.g., body language, facial expression) to gauge employee authenticity, rather than other cues (e.g., verbal, text) that can be more easily managed (Hennig-Thurau et al. 2006; Marinova, Singh, and Singh 2018). Nonverbal cues (e.g., social, facial expressions, body language) thus can have more than four times the impact on first impressions, compared with verbal cues or actual spoken information (Goman 2008). In addition, FTF communication forces both parties to pay more attention, because appearing inattentive would be contrary to well-established social norms (Goman 2011). Later in the relationship, these rich cues are no longer as important, because both parties have formed solid impressions and mental models, understand each other's needs, and have a well-developed relationship foundation (Ahearne, Gruen, and Davis 1999).

H_3: The effect of onboarding encoding on performance is greater for richer than leaner channels, such that (a) onboarding $\text{encoding}_{\text{FTF}}$ > onboarding $\text{encoding}_{\text{phone}}$, (b) onboarding $\text{encoding}_{\text{FTF}}$ > onboarding $\text{encoding}_{\text{email}}$, and (c) onboarding $\text{encoding}_{\text{phone}}$ > onboarding $\text{encoding}_{\text{email}}$.

Following similar arguments, the onboarding carryover effect should be greater for richer versus leaner channels. Again, FTF is the richest communication channel, with the most cues (e.g., verbal, visual), synchronicity, high level of personal focus, and natural varied language (Daft and Lengel 1986). These characteristics make interactions more memorable, with longer-lasting effects than those of contacts through leaner channels with fewer cues. Social norms require parties to pay attention during FTF communication (Goman 2011), and these attentive parties likely internalize message content, which also can help increase recall of prior communications (Hollingshead 1998). In contrast, leaner channels offer fewer cues for anchoring information and are asynchronous, which makes them less engaging and harder to remember. These leaner channels also may discourage sharing of relevant information, so the information exchange becomes less interactional and less likely to be remembered (Hollingshead 1998; Lewis 2004). Fewer cues also might reduce retrieval rates relative to having more memory cues. Finally, customers tend to perceive a company's use of more costly communication channels as a proxy for relationship investments, and FTF is the costliest channel, followed by telephone and then email. Face-to-face communication thus may trigger reciprocal feelings and behaviors that persist over time (Palmatier et al. 2008). Thus, the effect of onboarding carryover should increase with channel richness.

H_4: The effect of onboarding carryover on performance decays more slowly for richer than for leaner communication channels (i.e., *onboarding richness carryover*), such that (a) onboarding $\text{carryover}_{\text{FTF}}$ > onboarding $\text{carryover}_{\text{phone}}$, (b) onboarding $\text{carryover}_{\text{FTF}}$ > onboarding $\text{carryover}_{\text{email}}$, and (c) onboarding $\text{carryover}_{\text{phone}}$ > onboarding $\text{carryover}_{\text{email}}$.

Methodology

Sample

The data for this research come from a large *Fortune* 500 financial services firm that sells a large array of financial products and services across multiple business lines. Our random sample consists of 201,398 retail banking customers, whose face-to-face (FTF), telephone (PH), and email (EML) contacts were tracked for a 20-month period (January 2014–August 2015), resulting in 3,122,546 monthly observations. Selecting a sample of customers who began their relationship with the firm at the same time is necessary to study onboarding. First, it supports a comparison of multichannel communication effectiveness, during and after the onboarding period. Second, it includes the entire history of customer–firm communication, from the very inception of the relationship, mitigating the chances that we might overlook important prior interactions. Third, this approach eliminates left-truncation and survivorship biases, which can occur when customers drop out of the study prior to sample selection. The data were aggregated at a monthly level, because communication was sparse at the daily level; few multichannel communications occurred on the same day, so a daily approach would preclude assessments of multichannel interactions (Venkatesan and Kumar 2004).

Measurement

Multichannel communication. We operationalize multichannel communication as the number of communication contacts per channel per month for each customer, or communication frequency. The measure is specific to marketing and relationship-building efforts; it excludes transactional interactions (e.g., ATM withdrawals), which we include as a control variable. We only consider communication that results in an actual exchange between customers and the firm; unopened emails or missed phone calls are excluded from our analysis.

Share of wallet. The dependent variable, *customer share of wallet* (SOW), is the total proportion of the customer's financial assets allocated to the focal firm. This measure captures the broad effects of a better customer relationship with the firm more accurately than other financial measures, such as changes in sales or balances, which can be misleading when customers open accounts with minimal balances (e.g., $500 in a new checking account) or maintain large balances with other firms. It also integrates competitive effects while still capturing the ceiling effects of sales to individual customers. We operationalize SOW as the customer's total assets (deposits + investments) with the focal firm, divided by the customer's total assets across all financial institutions (total asset wallet). The latter were obtained from the focal firm's IXI Wealth Complete database. Table 2 provides a list of constructs and effects, definitions, and operationalizations, and Table 3 provides a summary of means, standard deviations, and correlations among key constructs.

Model Specification

We specify our empirical model sequentially, in accordance with its conceptual development. First, we describe the baseline model, which captures the known effects of communication on performance. It includes (1) linear and quadratic terms to capture inverted U-shaped relationships, (2) interactions among all communication channels, (3) stock variables to capture the effects of past communication, and (4) control variables to account for observed heterogeneity. Second, we specify the two hypothesized onboarding mechanisms, such that we evaluate dynamic onboarding effects while controlling for known communication effects. Third, we take steps to control for endogeneity.

Modeling known communication effects. We define SOW_{it} as customer i's observed share of wallet (SOW) at time t. Because SOW is constrained between 0% and 100%, we use a doubly censored regression (Tobit) framework and model SOW as a function of the communication contact variables. Then we can define SOW_{it*} as a customer's latent share of wallet, mapped to the observed share of wallet as follows:

$$(1) \qquad SOW_{it*} = \alpha_i + \mathbf{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it}^{SOW},\ \varepsilon_{it}^{SOW} \sim N\left(0, \sigma_{SOW,SOW}\right)$$

$$\begin{aligned} SOW_{it} &= 0 \text{ if } SOW_{it*} \leq 0 \\ SOW_{it} &= SOW_{it*} \text{ if } 0 < SOW_{it*} < 100 \\ SOW_{it} &= 100 \text{ if } SOW_{it*} \geq 100 \end{aligned}$$

where β represents the vector of parameter estimates, and $\mathbf{x_{it}}$ represents the vector of covariates corresponding to customer i's communication contact at time t. We account for unobserved customer heterogeneity by adopting a random intercepts approach, such that the intercepts can vary across each customer i:

$$(2) \qquad \alpha_i \sim N\left(\mu, \tau^2\right),\ i = 1 \ldots N.$$

As part of our baseline model, we include main effects for FTF_{it}, PH_{it}, and EML_{it}, as well as stock variables for one-period lagged FTF_{it}, PH_{it}, and EML_{it} so that we can separately estimate the effects of both current and past channel communication on SOW. We detail the stock variable formulation when describing our modeling approach for onboarding carryover. The quadratic terms in our modeling framework replicate prior research: FTF_{it}^2, PH_{it}^2, and EML_{it}^2. A negative, statistically significant squared term implies an inverted U-shaped relationship between that channel's frequency and SOW. We also include all two-way interactions among the three communication channels: $FTF_{it}\times PH_{it}$, $FTF_{it}\times EML_{it}$, and $PH_{it}\times EML_{it}$.

In addition to accounting for unobserved heterogeneity, we rely on control variables to account for observed heterogeneity: (1) lagged SOW (one time period), (2) total transactions, (3) total number of accounts, (4) customer is a mobile banking user, (5) log(total loan balances), and (6) customer age. The control variable of total transactions explicitly accounts for all customer service interactions (e.g., ATM visit, cashing a check), so we can isolate the effect of communication from basic financial transactions. Lagged SOW helps control for SOW stickiness (inertia over time), and the other control variables account for customer characteristics.

Modeling onboarding encoding. We model and test for the effect of onboarding encoding by creating a covariate for onboarding, $ONBOARD_{it}$, defined explicitly as a function of time ($TIME_{it}$) and a decay parameter δ, which is constrained to lie between 0 and 1:[3]

$$(3) \qquad ONBOARD_{it} = \left[\frac{\exp(\delta)}{1+\exp(\delta)} \right]^{(TIME_{it} - 1)}, \; 1 \leq TIME_{it} \leq 20.$$

Here, δ is updated iteratively, along with all other unknown parameters, in a Markov chain Monte Carlo (MCMC) estimation framework. At time = 1, the onboarding covariate is always equal to 100%. Thereafter, it decays to 0%. The inverse logit value of δ determines the rate at which the onboarding covariate decays. For example, if exp(δ)/(1 + exp(δ)) = .7, the values of the covariate $ONBOARD_{it}$ through the first three periods are {100%, 70%, 49%}. Larger values for δ imply a longer onboarding encoding window; smaller values imply faster decay and a shorter onboarding window. If exp(δ)/(1+exp(δ)) ≈ 0, there is essentially no onboarding encoding effect. To check for any additional beneficial impact of channel communication during the onboarding period, we also include interactions in our model: $ONBOARD_{it} \times FTF_{it}$, $ONBOARD_{it} \times PH_{it}$, and $ONBOARD_{it} \times EML_{it}$. The parameter estimates of these interactions indicate how much more beneficial early communication may be, compared with later communication, for each channel. Because $ONBOARD_{it}$ is a percentage covariate that starts at 100% and decays to 0% over time, any incremental communication benefits of encoding (i.e., positive parameter estimates) also dissipate to 0. With this functional form, we can estimate a

[3] We use an inverse logit transformation exp(δ)/(1 + exp(δ)) to constrain the values of δ to lie between 0 and 1.

permanent or baseline effect separately for each communication variable, as well as a temporary onboarding encoding effect that decays to 0% over time (e.g., $ONBOARD_{it} \times FTF_{it}$).

Modeling onboarding carryover. We capture the impact of onboarding carryover by using stock variables for FTF, PH, and EML. We first consider a typical stock variable formulation for a generic variable X:

$$\text{(4)} \qquad \text{Stock } X_t = X_t + \lambda X_{t-1} + \lambda^2 X_{t-2} + \lambda^3 X_{t-3} + \ldots + \lambda^{t-1} X_1,\ 0 < \lambda < 1,$$

such that we assume the carryover effect λ is constant over time and determines the extent to which past communication accumulates to affect the current period (Köhler et al. 2017; Nerlove and Arrow 1962). We extend this basic stock model by allowing for onboarding carryover. Previous research assumes a time-constant carryover parameter λ (Köhler et al. 2017; Koyck 1954); we instead allow our carryover parameter λ_t to vary over time in the modeling framework. Our hypotheses suggest that carryover effects may not be constant but rather might be greater earlier in the relationship. The onboarding carryover effect implies that $\lambda_t \geq \lambda_{t+1}$ for all t, because earlier communication imposes at least as great a carryover effect as later communication, all else being equal. Therefore, we account for onboarding carryover by rewriting Equation 4 with time-varying carryover parameters:

$$\text{(5)} \qquad \text{Stock } X_t = X_t + \lambda_{t-1} X_{t-1} + \lambda_{t-1}\lambda_{t-2} X_{t-2} + \lambda_{t-1}\lambda_{t-2}\lambda_{t-3} X_{t-3} + \ldots + \lambda_{t-1}\lambda_{t-2}\lambda_{t-3} \times \ldots \times \lambda_1 X_1,$$

$$\text{Where: } \lambda_t = \frac{\exp(\kappa_t)}{1 + \exp(\kappa_t)},\ \kappa_t = \pi_0 - \exp(\pi_1) \times (t-1).$$

In our regression, π_0 represents the intercept (unconstrained carryover effect in the first month, when t = 1), and $-\exp(\pi_1)$ is the unconstrained expected decrease in the carryover effect as t increases.[4] If $-\exp(\pi_1)$ is small, the carryover effect is essentially constant over time, and onboarding carryover does not exist ($\lambda_t \approx \lambda$ for all t). If $-\exp(\pi_1)$ is significantly negative, carryover effects decrease with the passage of time ($\lambda_t > \lambda_{t+1}$), offering evidence of onboarding carryover. We estimate separate slope and intercept parameters for each communication variable (FTF, PH, and EML), to determine whether some or all communication channels exhibit any onboarding carryover effects. We lag the stock variable by one period (Stock X_{t-1}) to separate the effects of current and past richness of each communication channel.

Modeling endogeneity. To account for endogeneity, we adopt a Bayesian instrumental variables approach (Lopes and Polson 2014). In line with previous research (Germann, Ebbes, and Grewal 2015; Kumar, Leszkiewicz, and Herbst 2018), we account for potential endogeneity among the three communication channel variables (FTF, telephone, and email) using a peer-based set of instruments, as we detail in Appendix 1.

Full Share-of-Wallet (SOW) Model

The full SOW model with all covariates may be written as follows:

$$
\begin{aligned}
(6)\quad SOW_{it*} = {} & \alpha_i + \beta_1 FTF_{it} + \beta_2 PH_{it} + \beta_3 EML_{it} && \text{(intercept and main effects (ME))}\\
& + \beta_4 FTF_{it}^2 + \beta_5 PH_{it}^2 + \beta_6 EML_{it}^2 && \text{(quadratic effects)}\\
& + \beta_7 FTF_{it}\times PH_{it} + \beta_8 FTF_{it}\times EML_{it} + \beta_9 PH_{it}\times EML_{it} && \text{(multichannel interactions)}\\
& + \beta_{10} \text{Stock } FTF_{i(t-1)} + \beta_{11} \text{Stock } PH_{i(t-1)} && \text{(stock variables)}\\
& + \beta_{12} \text{Stock } EML_{i(t-1)} && \\
& + \beta_{13} ONBOARD_{it} + \beta_{14} ONBOARD_{it}\times FTF_{it} && \text{(onboarding ME and interactions)}\\
& + \beta_{15} ONBOARD_{it}\times PH_{it} + \beta_{16} ONBOARD_{it}\times EML_{it} && \\
& + \beta_{17} SOW_{i(t-1)} + \beta_{18} TOTTRANS_{it} + \beta_{19} TOTACCT_{it} && \text{(control variables)}\\
& + \beta_{20} MOBILE_{it} + \beta_{21} LOGTOTLOAN_{it} && \\
& + \beta_{22} CUSTAGE_{it} && \\
& + \varepsilon_{it}^{SOW} && \text{(error term)}
\end{aligned}
$$

Model Estimation

[4] We constrain λ_t to lie in the interval (0, 1) through an inverse logit transformation.

We adopt a fully Bayesian approach to estimate the simultaneous impacts of the communication channels, control variables, instruments, stock variables, onboarding encoding, and onboarding carryover effects on SOW over time. The MCMC sampling algorithm enables us to estimate the model parameters, using a Metropolis-Hastings step, along with data augmentation (Tanner and Wong 1987). We use diffuse priors for all estimated parameters. After running the MCMC simulation for 20,000 draws, we discard the first 8,000 samples as the burn-in period. The MCMC chains achieve stationarity well before the end of this burn-in period. Furthermore, we thinned the MCMC chains to remove autocorrelation between draws, such that we retained every sixth draw in the stationary period for subsequent analysis. Methodologically, our approach simultaneously accounts for endogeneity, continuous onboarding encoding effects, onboarding carryover (time-varying carryover parameters), and data censoring. Appendix 2 provides the full details of the MCMC sampler.

Results

We investigate the effects of multichannel communication on performance while replicating known communication effects, to isolate the impact of multichannel onboarding dynamic effects and richness effects. Table 4 reports the results from estimating Equation 6.

Known Communication Effects

With non-hypothesized replications, we find support for inverted U-shaped relationships for both FTF ($\beta_{FTF}{}^2$ = -.18, 95% posterior interval [PI] = [-.21, -.14]) and telephone ($\beta_{telephone}{}^2$ = -.13, 95% PI = [-.21, -.05]) communication channels, in line with extant research. However, we find no support for inverted U-shaped effects for email ($\beta_{email}{}^2$ = .00, 95% PI = [.00, .01]). We identify significant multichannel substitution effects (negative interaction) for FTF × email

($\beta_{FTF \times email}$ = -.07, 95% PI = [–.10, –.04]) and telephone × email ($\beta_{telephone \times email}$ = –.13, 95% PI = [–.19, –.07]). Although the sign for FTF × telephone is negative, its 95% PI covers 0, so it is not significant ($\beta_{FTF \times telephone}$ = -.12; 95% PI = [-.27, .03]).

Furthermore, FTF communication exerts a greater main effect than telephone or email. The 95% PI of the differences, ($\beta_{FTF} - \beta_{telephone}$) and ($\beta_{FTF} - \beta_{email}$), are [2.55, 3.41] and [.94, 1.41], respectively—both positive and exclude 0. We also find that richer channels exert stronger past communication effects than do leaner channels ($\beta_{stock\ FTF} - \beta_{stock\ telephone}$ = .17, 95% PI = [.09, .23]; $\beta_{stock\ FTF} - \beta_{stock\ email}$ = .37, 95% PI = [.34, .40]; $\beta_{stock\ telephone} - \beta_{stock\ email}$ = .20; 95% PI = [.14, .26]). These results, which are consistent with findings from past research regarding known effects, increase confidence in the nomological validity of our conceptual and empirical models.

Onboarding Dynamic Effects

The results also demonstrate clear onboarding benefits. The onboarding decay encoding parameter, $\exp(\delta)/(1+\exp(\delta))$, is .81 (95% PI = [.81, .82]), indicating the presence of an onboarding effect in addition to known communication effects. The main effect of onboarding also is highly significant ($\beta_{onboarding}$ = 9.89; 95% PI = [9.72, 10.07]), such that in the absence of any communication, a customer's baseline SOW shifts upward by almost 10%, implying a "honeymoon" relationship phase. Apparently, even without any early interactions, customers tend to start strongly, but over time, the relationships begin to fade.

Consistent with H_1, communicating earlier in the relationship, during the onboarding period, enhances the effect of communication frequency on performance ($\beta_{onboarding \times FTF}$ = 3.02, 95% PI = [2.82, 3.22]; $\beta_{onboarding \times telephone}$ = 2.69, 95% PI = [2.30, 3.08]; $\beta_{onboarding \times email}$ = 1.11, 95% PI = [1.03, 1.19]). Thus, in support of $H_{1a–c}$, communication's effect on performance is temporarily enhanced at the beginning of the relationship, in an encoding effect that is additional to the known communication effects and is temporary, in that it dissipates as the relationship ages.

Regarding onboarding carryover, Equation 5 shows that carryover effects decrease over time if $-\exp(\pi_1)$ is significantly negative and different from 0. Values of $-\exp(\pi_1)$ close to 0 suggest time-constant carryover effects. We accordingly report posterior estimates for $-\exp(\pi_1)$ in Table 4. In strong support of all three predictions in H_2, channel carryover effects decrease over time. All three effects are significantly negative and different from 0 ($-\exp(\pi_{1,FTF}) = -.28$, 95% PI = [-.36, -.21]; $-\exp(\pi_{1,telephone}) = -3.26$, 95% PI = [-3.46, -3.09]; $-\exp(\pi_{1,email}) = -1.55$; 95% PI = [-1.69, -1.33]). Thus, communication's carryover effect is greatest at the beginning of the relationship and decreases over time, as the relationship ages.

Onboarding Richness Effects

The effect of onboarding encoding is greater in the FTF channel than for email ($\beta_{onboarding \times FTF} - \beta_{onboarding \times email} = 1.91$; 95% PI = [1.69, 2.13]), in support of H_{3b}. The effect of onboarding encoding is also greater for the telephone channel than for email ($\beta_{onboarding \times telephone} - \beta_{onboarding \times email} = 1.58$; 95% PI = [1.17, 1.99]), in support of H_{3c}. However, the 95% PI of $\beta_{onboarding \times FTF} - \beta_{onboarding \times telephone}$ includes 0, so we cannot confirm H_{3a}.

The onboarding carryover effects for FTF also decay more slowly over time than the carryover effects for telephone or email, consistent with H_{4a} and H_{4b} ($-\exp(\pi_{1,FTF}) - (-\exp(\pi_{1,telephone})) = 2.98$, 95% PI = [2.78, 3.23]; $-\exp(\pi_{1,FTF}) - (-\exp(\pi_{1,email})) = 1.29$, 95% PI = [1.06, 1.46]). However, we do not find support for H_{4c}, because the onboarding carryover effects for telephone do not appear to decay more slowly than the carryover effects for email.

Controls

The estimates of the control variables are all significant. The lagged SOW (β = .71, PI = [.71, .71]) indicates an inertial effect of past SOW; approximately 71% of the customer's SOW from the previous month carries forward to current month SOW. As expected, total transactions (β = .09, PI = [.09, .09]) have a positive impact on SOW. Similarly, the total number of accounts (β = 6.31, PI = [6.24, 6.38]) and mobile banking user (β = 4.03, PI = [3.84, 4.21]) variables are both positive. Finally, customers who have larger total loan balances (β = -2.25, PI = [-2.27, -2.23]) and older customers (β = -.12, PI = [-.12, -.11]) exhibit lower SOWs.

Effective Multichannel Onboarding Strategies

The results for the effects of multichannel communication onboarding on performance suggest the critical need to incorporate both onboarding (encoding and time-varying carryover) and richness effects to obtain a full understanding of communication effects on performance. To generate more actionable guidance, we supplement our hypotheses testing with a series of supplementary analyses that offer additional insights into the magnitude of these effects, as well as generate specific guidance for deriving effective multichannel onboarding strategies.

Customer Onboarding: Decomposition, Magnitude, and Duration of Effects

In Figure 2 we decompose the total marginal effect on the SOW of an average customer in our sample due to one additional FTF communication (Panel A) and one additional email communication (Panel B), using three types of effects: (1) permanent (non-onboarding effects), (2) onboarding encoding, and (3) onboarding carryover.[5] In the first month, 91% of the total marginal impact of one additional FTF communication and one additional email came from the onboarding versus permanent effects (i.e., only 9% is due to the permanent effect for either

[5] Because the non-onboarding (permanent) effect of telephone is not significantly different from 0, we only plot the comparisons for Figure 2 between FTF (richest channel) and email (leanest channel).

channel). Early in the relationships, the *onboarding encoding* dominates the overall effect, accounting for 58% of the total effect for FTF and 82% for email in Month 1. Then the *onboarding carryover* surpasses the encoding effect as the more important component in Month 4 for FTF and Month 24 for email. These results highlight the importance of each effect at different points in time and by channel. Encoding is critical early, as customers are beginning their mental models of the firm, but carryover lasts longer and is key for extending the onboarding window when the mental model is being used to make decisions. After the onboarding effects dissipate, communication's permanent or "non-onboarding" effects dominate for the rest of the relationship in both channels.

The *onboarding window* or onboarding half-life—defined as a period of time that it takes for 50% of the onboarding communication benefits to dissipate (i.e., no longer available for firms to leverage)—occurs after 4.4 months for FTF and 4.6 months for email.[6] However, it takes 15.0 months for FTF and 11.5 months for email before 90% of the onboarding benefits dissipate, which reinforces the resilience of first impressions and customer's initial mental models. In this sample, the onboarding half-life is approximately four months, with an onboarding expiration date of about one year (FTF enjoys a slightly longer onboarding window, due to longer lasting carryover benefits). Communication efforts after one year largely do not experience the onboarding lift derived from building a strong relationship foundation.

Recognizing that onboarding benefits are temporary, we also offer some managerial insights into the relative importance of onboarding during the first five years of the relationship on an average customer's SOW. We assume that a customer receives one FTF communication and one email communication every month for the first 60 months and evaluate the total impact by channel across the three effect types. Although most of the encoding and onboarding

[6] These calculations incorporate the decay effects of both onboarding encoding and carryover.

carryover dissipate after the first year, they still comprise 21% and 30% of the total cumulative benefit of FTF communication over five years (51% of total effect due to onboarding) and 35% and 11% for email (46% due to onboarding). Thus, evaluating consistent monthly communication across a full five-year period, the extra lift from onboarding still accounts for *roughly half of the total net benefit for each channel*. That is, communicating in the onboarding window can have significant financial effects, and missing the non-recoverable communication leverage during onboarding can significantly reduce performance even after 5 years.

Relative Effectiveness of Communication Richness Strategies

In Figure 3, we compare the relative effectiveness of the different communication channels for increasing SOW as relationships age. Specifically, we note the total impact of one additional FTF, telephone, and email communication by month for the first two years and the expected change in the SOW for an average customer. These calculations include the sum of permanent (i.e., non-onboarding or known effects), onboarding encoding, and onboarding carryover effects. Although FTF communication should have a greater benefit than either phone or email, these benefits are especially noticeable early, as revealed by the greater vertical distance between FTF and the other two channels in Figure 3 early in the relationship. *FTF communication has a 19 times greater impact on performance in the first month compared with just two years later* (after the onboarding window).

Overall, richer communication channels are better at leveraging onboarding benefits and should be used with greater frequency earlier in the relationship. Because telephone has very small permanent benefits, once the onboarding window has closed, there is minimal benefit of using telephone over email channels in our sample. This somewhat surprising finding seems consistent with research that identifies telephone communication as overly intrusive and a "dying institution" (Kluger 2012, p. 1), but it also requires additional investigation, to confirm whether the richness costs of the telephone channel outweigh its benefits as relationships age.

Onboarding Insights for Multichannel Complementarities vs. Substitutive Interaction Effects

We conducted supplementary analyses to determine if onboarding effects may explain inconsistencies in prior research regarding multichannel interactions (Godfrey, Seiders, and Voss 2011; Reinartz, Thomas, and Kumar 2005). Communication channels might offer positive interactions in the onboarding window, reflecting the complementary characteristics of the different channels (e.g., visual cues in FTF, revisability in email), which help a new customer build a stronger mental model. However, after the onboarding period, communication mostly serves to enhance the customer's understanding relative to both a pre-established baseline of knowledge and perceived costs (e.g., customer time, hassle, cognitive effort). Thus, different channels may come to substitute for one another (negative interactions). Many of the complementarities among channels may be most valuable when partners are highly attentive, willing to process and integrate multichannel data during the encoding stage in their onboarding period.

To test this premise explicitly, we reran our model with interactions of onboarding with each pair of communication channels (onboarding×FTF×telephone, onboarding×FTF×email, and onboarding×telephone×email). All the multichannel interaction effects switch from being complementary (positive interactions) to being substitutive (negative interactions) over time, as we depict in Figure 4 (for detailed results and the breakeven analysis, see Appendix 3). According to the breakeven analysis, the tipping point, at which the interactions switch from complementary to substitutive, occurs at 4.5 months for FTF×telephone, 5.7 months for FTF×email, and 4.3 months for telephone×email. Customer relationships that are less than about five or six months long tend to exhibit positive interactions (multichannel complementarity), while those older than six months exhibit negative interactions (multichannel substitution). Consistent with most extant research, our sample includes more communication interactions beyond the onboarding window, which helps explain why the parameter estimates for the multichannel interactions are all negative in our overall model. That is, onboarding appears to be a critical moderator of multichannel interactions, explaining past findings for both complementary and substitutive interactions. The posterior estimates for the two channel interactions involving onboarding and FTF are larger, which suggests another benefit of onboarding for FTF communication, namely, greater positive multichannel interactions during the onboarding window.

Figure 4 plots the breakeven points for each multichannel interaction, including both expected marginal gains (greater than 0) in SOW that accrue from operating in the positive interaction (complementarity) region and the expected marginal losses in SOW due to operating in the negative interaction (substitution) region. The losses from operating in the substitution region are significantly greater than the associated gains obtained from operating in the synergy region. Thus, multichannel interactions are a double-edged sword: They can reap some additional positive benefits if implemented early in the relationship, but these benefits can easily be overshadowed by the use of too many channels simultaneously, later in the relationship. Finally, the losses appear especially great for the FTF×telephone interaction (Figure 4, Panel A); too much channel richness and its high costs (time, effort, social) likely has the most counterproductive effects after onboarding.

Onboarding Insights for Customer Future Performance Trajectories

Onboarding has important implications for the future trajectories of customers as well. In order to demonstrate the impact of onboarding on an average customer's future relationship, Figure 5 illustrates the collective impact of one additional FTF, telephone, and email communication on current SOW as well as on future SOW for up to 12 months into the future. We plot the marginal impact of these communication pulses for Months = 1, 6, and 12. For example, the line corresponding to Month = 1 shows the marginal impact of one additional FTF, telephone, and email communication occurring at Month = 1 on SOW for the customer's relationship starting from Month 1 and up to Month 13; The line corresponding to Month = 12 shows the marginal impact of one additional FTF, telephone, and email communication occurring at Month = 12 on SOW for the customer's relationship starting from Month 12 and up to Month 24. We also include a baseline customer trajectory for comparison purposes which excludes any communication to show how the average customer's relationship evolves in the absence of any communication. Figure 5 demonstrates that early intervention has a much larger impact on both the customer's current and future trajectories. For example, one additional FTF, telephone and email communication occurring only in Month 1 has a noticeable impact on the customer's SOW trajectory 12 months later; however if that same communication were to occur in Month 12 it has a negligible impact on the customer's trajectory 12 months later (when compared to the "No communication" alternative). Onboarding communications therefore have important implications not only for building current customers' relationships but also for influencing their future relationships.

Discussion

Theoretical Implications

Our research defines, theoretically develops, and tests an important new construct for the marketing domain: *customer onboarding*. This construct has been emphasized by marketing practitioners, but research into customer onboarding is largely absent from the academic domain (Voorhees et al. 2017). We identify some key elements of onboarding and use first impression and relationship marketing dynamics theories to explicate how and why early communication matters more. Onboarding effects consist of two key mechanisms: encoding and carryover. In introducing the notion of time-varying onboarding carryover effects, we also demonstrate that they are not constant, as predicted by most previous research (Clarke 1976; Köhler et al. 2017; Koyck 1954), but rather are greater early in the customer relationship.

Our research also provides the first empirical estimation of the magnitude and duration of onboarding, which operates differently across various communication channels according to their degree of richness. Richness matters more during onboarding; we also introduce and quantify the length of the onboarding window, which is critical for understanding when the onboarding benefits disappear. This research thus highlights the importance of an understudied topic in the relationship marketing and communication domains, indicating the need for additional academic research that incorporates these dynamic onboarding effects.

We also reconcile some debates in prior academic research. With a dynamic approach, we establish the pivotal role of onboarding in determining whether multichannel interactions are complementary or substitutive. Both positive and negative interactions found in past research are valid; there are positive interaction effects among communication channel pairs while the relationship remains relatively new, but after a certain amount of time, these interactions convert into negative multichannel substitutive effects. Finally, we demonstrate that *onboarding benefits enhance the effect of early communication on performance in four ways* during a finite window:

(1) onboarding encoding effect, (2) onboarding carryover effect, (3) positive multichannel interactions, and (4) enhancement of richer communication channels.

Managerial Implications

These results and supplemental analyses provide rich managerial insights regarding how to design effective multichannel onboarding strategies. Some white papers imply that onboarding is nothing more than a series of "welcome aboard" activities (Pugnetti and Bekaert 2018), but our research reveals a subtler effect, entailing both relational mental model building/encoding and use/carryover mechanisms. Onboarding also has an important temporal component. By quantifying the onboarding window, we demonstrate that about 50% of onboarding benefits are no longer accessible after just four months, and 90% are lost after about a year. Because communication is more effective early on, managers should devote additional communication resources to nurturing new customer relationship foundations, to leverage their longer-lasting effects. For example, FTF and email communication have, respectively, 19 times and 14 times greater impacts on SOW in the first month than they do two years later. Customer lifetime value (CLV) models also might benefit from incorporating dynamic onboarding effects, because the same firm intervention strategies may have different CLV implications if performed early, during onboarding versus later in the relationship.

To our knowledge, this research is the first to introduce and explicitly incorporate onboarding (time-varying) carryover effects. The notion of carryover effects is not new to managers or researchers, and clearly, the benefits of communication may carryover over multiple periods (Hanssens, Parsons, and Schultz 2001). However, many managerial implementations of carryover effects, such as Adstock (Broadbent 1979), reflect an assumption that carryover is constant and unaffected by onboarding. We show instead that carryover effects are significantly greater during onboarding, so managers should consider broadening the time horizons they use to determine the full impact of their marketing communications on performance metrics during onboarding. Failing to do so may lead to underestimates of the true value of communication strategies.

Our research also demonstrates the importance of using richer channels, which benefit proportionally more during onboarding. Managers should note the incremental benefits of richer communication carefully; many firms are shifting resources away from richer communication channels in favor of leaner, more "cost-effective" channels (Durmaz and Efendioglu 2016). But doing so entails an opportunity cost, because even if leaner communications are cheaper, they cannot reap the full benefits of rich, early communication. For example, leaner communication may be unable to build sufficient loyalty early on, preordaining customers to subpar relational trajectories for their entire multi-year relationship. Because onboarding benefits are available for a limited time only (i.e., "you only get to make a first impression once"), firms that fail to capitalize on the relationship-building benefits of rich, early communication may not be able to reap the benefits later in the exchange either.

Limitations and Research Directions

This research has several limitations. We tested our conceptual framework with a single financial services firm, and future multichannel communication research should investigate the impact of firm-level variables on performance outcomes using data from multiple firms. The financial services context supports a comprehensive test of multichannel communication and onboarding, because it features different channels, and it is clear when customers onboard with the firm. Still, additional research might investigate this phenomenon in other industries, to generalize and elaborate on our findings.

Communication also is influenced by cultural norms (Samaha, Beck, and Palmatier 2014), so researchers could investigate the impact of various cultures on onboarding (Do some cultures onboard more quickly than others? How does onboarding affect different cultural groups?). We also focused on the quantity or frequency of communication, but to enhance understanding of multichannel communication and onboarding, further research could incorporate the quality or content of communication into its theoretical frameworks.

Appendix 1

DETAILS OF THE ENDOGENEITY CORRECTION

Addressing Endogeneity

Because firms may strategically determine the amount of communication to send to each customer in a non-random way, the communication may be endogenous. For example, firms may choose to communicate more with customers it regards as more desirable, based on some predetermined criteria that are unavailable to us. Because we lack full information about all of the inputs to the firm's decision-making processes, omitted variables may create correlations of each marketing communication channel variable with the error term. To address this potential endogeneity concern, we apply a full Bayesian instrumental variable (IV) approach (Lopes and Polson 2014). The structural form of our model is:

$$\begin{aligned} SOW_{it*} &= \alpha_i + \mathbf{x}'_{\mathbf{it}}\boldsymbol{\beta} + \varepsilon_{it}^{SOW} \\ FTF_{it} &= \mathbf{z}'_{\mathbf{it,FTF}}\boldsymbol{\gamma}_{\mathbf{FTF}} + \varepsilon_{it}^{FTF} \\ PH_{it} &= \mathbf{z}'_{\mathbf{it,PH}}\boldsymbol{\gamma}_{\mathbf{PH}} + \varepsilon_{it}^{PH} \\ EML_{it} &= \mathbf{z}'_{\mathbf{it,EML}}\boldsymbol{\gamma}_{\mathbf{EML}} + \varepsilon_{it}^{EML} \end{aligned} \tag{A1}$$

where $\mathbf{z}_{\mathbf{it,X}}$ captures the vector of instruments used, and $\gamma_{\mathbf{X}}$ captures the respective parameter estimates for each potentially endogenous communication variable, $X \in \{FTF, PH, EML\}$. To complete the IV specification, we define the covariance structure between the error terms as:

$$\begin{pmatrix} \varepsilon_{it}^{SOW} \\ \varepsilon_{it}^{FTF} \\ \varepsilon_{it}^{PH} \\ \varepsilon_{it}^{EML} \end{pmatrix} \sim N\left[\begin{pmatrix} 0 \\ 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_{SOW,SOW} & \sigma_{SOW,FTF} & \sigma_{SOW,PH} & \sigma_{SOW,EML} \\ \sigma_{SOW,FTF} & \sigma_{FTF,FTF} & \sigma_{FTF,PH} & \sigma_{FTF,EML} \\ \sigma_{SOW,PH} & \sigma_{FTF,PH} & \sigma_{PH,PH} & \sigma_{PH,EML} \\ \sigma_{SOW,EML} & \sigma_{FTF,EML} & \sigma_{PH,EML} & \sigma_{EML,EML} \end{pmatrix}\right] = \boldsymbol{\Sigma} \tag{A2}$$

In line with previous research (Germann, Ebbes, and Grewal 2015; Kumar, Leszkiewicz, and Herbst 2018), we account for potential endogeneity among the three communication channel variables (face-to-face, telephone, and email) by developing a peer-based set of instruments.

Specifically, we create 100 groups of customer peers based on the quintiles of total customer balances, total transactions, and four brackets of number of accounts owned (1, 2, 3, or 4+ accounts). Next, for each customer and each time period, we assign customers to one of the 100 groups, and we calculate the average number of face-to-face communications, telephone calls, and emails to all customers in their respective group while excluding the focal customer from this calculation. We repeat this approach for every customer in our sample and for every time period. We then use the peer-averaged values as the respective instruments for face-to-face communication, telephone calls, and emails.

This peer-based IV approach is valid and reliable. As Table A1 indicates, the level of marketing communication to each customer cohort relates significantly to the level of communication targeting the focal customer. Firms likely design their communications to maximize value, so customers in similar profile brackets, defined by balances, transactions, or number of accounts, should receive similar communication efforts, because the cohorts capture some unobserved, value-maximizing decisions (Cooil et al. 2007; Kumar and Venkatesan 2005). Furthermore, these peer-constructed IV communication contact variables, based on each customer cohort, exclude the focal customer, so the instruments cannot exert a direct influence on each customer's SOW; they are unobservable to that focal customer. Thus, the exclusion restriction is satisfied. As an empirical check, we calculate the correlation between our peer-based IVs and the SOW dependent variable, and in all cases, the correlation is low ($r < .10$).

TABLE A1
The Impact of Instruments on Endogenous Communication Variables

Parameters	IV Models (Endogeneity Correction) Posterior Means		95% Posterior intervals	
Face-to-face communication equation				
Intercept	.00		[.00	.00]
Face-to-face peer-based IV	.99	**	[.98	.99]
Telephone communication equation				
Intercept	.00		[.00	.00]
Telephone peer-based IV	.96	**	[.96	.97]
Email communication equation				
Intercept	.00		[.00	.00]
Email peer-based IV	.99	**	[.99	1.00]

**More than 95% of the posterior distribution for estimate does not include zero.

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Appendix 2

MCMC SAMPLER

In the MCMC algorithm, non-informative priors are used throughout the estimation process.

1. Update latent SOW_{it^*}
2. Update intercept and slope parameters $\{\pi_{0,FTF}, \pi_{1,FTF}\}$, $\{\pi_{0,PH}, \pi_{1,PH}\}$, $\{\pi_{0,EML}, \pi_{1,EML}\}$, corresponding to the time-varying carryover effects: $\{\lambda_{t,FTF}, \lambda_{t,PH}, \lambda_{t,EML}\}$, and update the corresponding stock variables based on them
3. Update onboarding decay parameter δ, onboarding covariate ($ONBOARD_{it}$), and interactions of $ONBOARD_{it}$ with communication covariates ($ONBOARD_{it}\times FTF_{it}$, $ONBOARD_{it}\times PH_{it}$, and $ONBOARD_{it}\times EML_{it}$)
4. Update random intercepts α_i corresponding to the SOW equation
5. Update fixed effect regression parameters β corresponding to the SOW equation
6. Update the γ coefficients $\{\gamma_{\mathbf{FTF}}, \gamma_{\mathbf{PH}}, \gamma_{\mathbf{EML}}\}$ corresponding to the instruments for endogenous FTF, PH, and EML covariates
7. Update covariance matrix Σ
8. Update population mean parameter μ, which captures the mean of the sampling distribution for α_i
9. Update population variance parameter τ^2, which captures the variance of the sampling distribution for α_i

Step 1: Update latent SOW_{it^*}

a. Using the conditional distributional properties of the multivariate normal distribution (e.g. $X_1|X_2 \sim N(\mu_1 + \Sigma_{12}\Sigma_{22}^{-1}(X_2 - \mu_2), \Sigma_{11} - \Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21})$, define the conditional mean of SOW given all other endogenous variables:

$$\tilde{\mu}_{it,SOW} = \alpha_i + \mathbf{x}'_{it}\boldsymbol{\beta} + \begin{bmatrix}\sigma_{SOW,FTF} & \sigma_{SOW,PH} & \sigma_{SOW,EML}\end{bmatrix} \times \begin{bmatrix}\sigma_{FTF,FTF} & \sigma_{FTF,PH} & \sigma_{FTF,EML} \\ \sigma_{FTF,PH} & \sigma_{PH,PH} & \sigma_{PH,EML} \\ \sigma_{FTF,EML} & \sigma_{PH,EML} & \sigma_{EML,EML}\end{bmatrix}^{-1} \times \begin{bmatrix} FTF_{it} - \mathbf{z}'_{\mathbf{it,FTF}}\boldsymbol{\gamma}_{\mathbf{FTF}} \\ PH_{it} - \mathbf{z}'_{\mathbf{it,PH}}\boldsymbol{\gamma}_{\mathbf{PH}} \\ EML_{it} - \mathbf{z}'_{\mathbf{it,EML}}\boldsymbol{\gamma}_{\mathbf{EML}} \end{bmatrix} \tag{A3}$$

where $\mathbf{z_{it,FTF}}$, $\mathbf{z_{it,PH}}$, and $\mathbf{z_{it,EML}}$ are the instruments for FTF_{it}, PH_{it}, and EML_{it}, respectively.

b. Define the conditional variance of SOW, given all other endogenous variables, as:

$$\tilde{\sigma}^2_{SOW} = \sigma_{SOW,SOW} - \begin{bmatrix}\sigma_{SOW,FTF} & \sigma_{SOW,PH} & \sigma_{SOW,EML}\end{bmatrix} \times \begin{bmatrix}\sigma_{FTF,FTF} & \sigma_{FTF,PH} & \sigma_{FTF,EML} \\ \sigma_{FTF,PH} & \sigma_{PH,PH} & \sigma_{PH,EML} \\ \sigma_{FTF,EML} & \sigma_{PH,EML} & \sigma_{EML,EML}\end{bmatrix}^{-1} \times \begin{bmatrix}\sigma_{SOW,FTF} \\ \sigma_{SOW,PH} \\ \sigma_{SOW,EML}\end{bmatrix} \tag{A4}$$

c. If $SOW_{it} = 0$ (left censored case), draw $SOW_{it*} \sim \text{truncated normal}_{(-\infty,\, 0]}\left(\tilde{\mu}_{it,SOW},\ \tilde{\sigma}^2_{SOW}\right)$
d. If $SOW_{it} = 100$ (right censored case), draw
$SOW_{it*} \sim \text{truncated normal}_{[100,\, +\infty)}\left(\tilde{\mu}_{it,SOW},\ \tilde{\sigma}^2_{SOW}\right)$
e. If $0 < SOW_{it} < 100$ (uncensored case), set $SOW_{it*} = SOW_{it}$

Step 2: Update intercept and slope parameters corresponding to time-varying carryover effects and associated stock variables

a. Propose intercept and slope parameters for time-varying carryover effects corresponding to FTF communication $\pi_{0,FTF*}$ and $\pi_{1,FTF*}$:

$$\Pi_{F*} = \begin{pmatrix} \pi_{0,FTF*} \\ \pi_{1,FTF*} \end{pmatrix} \sim \text{bivariate normal}\left(\begin{bmatrix} \pi_{0,FTF(s)} \\ \pi_{1,FTF(s)} \end{bmatrix},\ \Sigma_{\pi F}\right) \tag{A5}$$

where $\Pi_{F*} = (\pi_{0,FTF*}, \pi_{1,FTF*})'$ are the proposed intercept and slope parameters, $\Pi_{F(s)} = (\pi_{0,FTF(s)}, \pi_{1,FTF(s)})'$ represent respectively the current (non-proposed) values for the intercept and slope parameters corresponding to the time-varying carryover effects $\lambda_{t,FTF}$, and $\Sigma_{\pi F}$ is a diagonal covariance matrix chosen to optimize the acceptance ratio.

b. Calculate the proposed values for the time-varying carryover effects $\lambda_{t,FTF*}$:

$$\lambda_{t,FTF*} = \frac{\exp\left\{\pi_{0,FTF*} - \exp\left(\pi_{1,FTF*}\right) \times (t-1)\right\}}{1 + \exp\left\{\pi_{0,FTF*} - \exp\left(\pi_{1,FTF*}\right) \times (t-1)\right\}} \tag{A6}$$

c. Calculate proposed stock variable values, Stock $FTF_{i(t-1)*}$, based on proposed time-varying carryover effects $\lambda_{t,FTF*}$ as[7]:

$$\begin{aligned} \text{Stock } FTF_{i(t-1)*} &= FTF_{i(t-1)} + \lambda_{(t-1),FTF*} \times FTF_{i(t-2)} + \lambda_{(t-1),FTF*} \times \lambda_{(t-2),FTF*} \times FTF_{i(t-3)} \\ &+ \lambda_{(t-1),FTF*} \times \lambda_{(t-2),FTF*} \times \lambda_{(t-3),FTF*} \times FTF_{i(t-4)} + \ldots + \lambda_{(t-1),FTF*} \times \lambda_{(t-2),FTF*} \times \ldots \times \lambda_{2,FTF*} FTF_{i1} \end{aligned} \tag{A7}$$

where the notation $\lambda_{t,FTF*}$ refers to the proposed value of λ at time t for FTF communication, based on Equations A5 and A6.

d. Define $\tilde{\mu}_{it,SOW}$ and $\tilde{\sigma}^2_{SOW}$ as in Equations A3 and A4. Define $\tilde{\mu}_{it,SOW*}$ as the conditional mean in Equation A3, using the newly proposed stock variable values derived in Equation A7.

e. Accept proposed stock variable values Stock $FTF_{i(t-1)*}$, time-varying carryover effect values $\lambda_{t,FTF*}$, and proposed intercept and slope parameters $\Pi_{F*} = (\pi_{0,FTF*}, \pi_{1,FTF*})'$ with the following acceptance probability r:

[7] Following our discussion in the manuscript, our stock variables are based on lagged (by one period) communication variables, in order to separately estimate the current effects of communication from the effects of past (stocked) communication.

$$r = \min\left\{1,\ \frac{\prod_{i=1}^{N}\prod_{t=1}^{T_i}\exp\left(-.5\times\left(SOW_{it*}-\tilde{\mu}_{it,SOW*}\right)^2/\tilde{\sigma}^2_{SOW}\right)\times\exp\left(-.5\times\left(\Pi_{F*}-\Pi_0\right)'\Psi_0^{-1}\left(\Pi_{F*}-\Pi_0\right)\right)}{\prod_{i=1}^{N}\prod_{t=1}^{T_i}\exp\left(-.5\times\left(SOW_{it*}-\tilde{\mu}_{it,SOW}\right)^2/\tilde{\sigma}^2_{SOW}\right)\times\exp\left(-.5\times\left(\Pi_{F(s)}-\Pi_0\right)'\Psi_0^{-1}\left(\Pi_{F(s)}-\Pi_0\right)\right)}\right\} \tag{A8}$$

where Π_0 and Ψ_0 represent the prior mean and covariance corresponding to vector ($\pi_{0,FTF}$ $\pi_{1,FTF}$)′, and Π_{F*} are the proposed values for ($\pi_{0,FTF*}$, $\pi_{1,FTF*}$)′, as defined in Equation A5. The stock variables and carryover parameters for PH and EML are updated similarly.

Step 3: Update onboarding decay parameter δ, the onboarding main effect covariate ($ONBOARD_{it}$), and associated interactions with communication covariates

a. Sample a proposal for the onboarding decay parameter δ_*: $\delta_* \sim N(\delta_{(s)}, \kappa_\delta)$, where $\delta_{(s)}$ represents the value of the current (non-proposed) onboarding decay parameter, and κ_δ is a tuning parameter chosen to optimize the acceptance ratio.

b. Calculate proposed onboarding main effect covariate, $ONBOARD_{it*}$ as:

$$ONBOARD_{it*} = \left[\frac{\exp(\delta_*)}{1+\exp(\delta_*)}\right]^{(TIME_{it}\ -\ 1)} \tag{A9}$$

where $TIME_{it}$ represents the elapsed time (number of months) since the inception of customer i's relationship (TIME = 1…20).

c. Given the proposed covariate $ONBOARD_{it*}$, calculate the proposed interaction terms with the communication variables: $ONBOARD_{it*}\times FTF_{it}$, $ONBOARD_{it*}\times PH_{it}$, and $ONBOARD_{it*}\times EML_{it}$.

d. Define $\tilde{\mu}_{it,SOW}$ and $\tilde{\sigma}^2_{SOW}$ as in Equations A3 and A4. Define $\tilde{\mu}_{it(\delta*)}$ as the conditional mean in Equation A3 but based on the newly proposed onboarding covariates calculated in Steps 3a, 3b, and 3c.

e. Accept the proposed onboarding decay parameter δ_*, proposed onboarding covariate $ONBOARD_{it*}$, and its associated interactions with the communication variables ($ONBOARD_{it*}\times FTF_{it}$, $ONBOARD_{it*}\times PH_{it}$, and $ONBOARD_{it*}\times EML_{it}$) with following acceptance probability r:

$$r = \min\left\{1,\ \frac{\prod_{i=1}^{N}\prod_{t=1}^{T_i}\exp\left(-.5\times\left(SOW_{it*}-\tilde{\mu}_{it(\delta*)}\right)^2/\tilde{\sigma}^2_{SOW}\right)\times\exp\left\{-.5\left(\delta_*\ -\ \delta_0\right)^2/\varsigma_0^{\ 2}\right\}}{\prod_{i=1}^{N}\prod_{t=1}^{T_i}\exp\left(-.5\times\left(SOW_{it*}-\tilde{\mu}_{it,SOW}\right)^2/\tilde{\sigma}^2_{SOW}\right)\times\exp\left\{-.5\left(\delta_{(s)}\ -\ \delta_0\right)^2/\varsigma_0^{\ 2}\right\}}\right\} \tag{A10}$$

where the parameters δ_0 and ζ_0^2 are the prior mean and variance for δ.

Step 4: Update random intercepts α_i for each customer i corresponding to the SOW equation

a. Define $\tilde{\mu}_{it,SOW}$ and $\tilde{\sigma}^2_{SOW}$ as in Equations A3 and A4. Then define
$$\tilde{y}_{it} = SOW_{it*} - \tilde{\mu}_{it,SOW} + \alpha_i \text{. Thus, } \tilde{y}_{it} \sim N\left(\alpha_i, \tilde{\sigma}^2_{SOW}\right). \tag{A11}$$

b. Define T_i as the total number of observations (time periods) observed for each customer i. Let μ and τ^2 describe the mean and variance of the distribution of α_i: $\alpha_i \sim N\left(\mu, \tau^2\right)$

c. For each customer i, i = 1, …, N, draw α_i from the following univariate normal distribution:
$$\alpha_i \sim \text{univariate normal}\left(\frac{T_i\bar{\tilde{y}}_i/\tilde{\sigma}^2_{SOW} + \mu/\tau^2}{T_i/\tilde{\sigma}^2_{SOW} + 1/\tau^2}, \left[T_i/\tilde{\sigma}^2_{SOW} + 1/\tau^2\right]^{-1}\right), \tag{A12}$$
where $\bar{\tilde{y}}_i = \frac{1}{T_i}\sum_{t=1}^{T_i}\tilde{y}_{it}$ is the sample mean of $\tilde{y}_{it}$ for customer i, and T_i represents the total number observations for customer i.

Step 5: Update the fixed effect regression parameters β corresponding to the SOW equation

a. Define $\tilde{\mu}_{it,SOW}$ and $\tilde{\sigma}^2_{SOW}$ as in Equations A3 and A4. Then define
$$\tilde{s}_{it} = SOW_{it*} - \tilde{\mu}_{it,SOW} + \mathbf{x}'_{\mathbf{it}}\boldsymbol{\beta} \text{. Then } \tilde{s}_{it} \sim N\left(\mathbf{x}'_{\mathbf{it}}\boldsymbol{\beta}, \tilde{\sigma}^2_{SOW}\right) \tag{A13}$$

b. Draw $\beta \sim$ multivariate normal (MVN) with the following mean and covariance:
$$\boldsymbol{\beta} \sim \text{MVN}\left(\left[\boldsymbol{\Sigma_0}^{-1} + \sum_{i=1}^{N}\sum_{t=1}^{T_i}\mathbf{x}_{\mathbf{it}}\mathbf{x}'_{\mathbf{it}}/\tilde{\sigma}^2_{SOW}\right]^{-1}\left[\boldsymbol{\Sigma_0}^{-1}\boldsymbol{\beta_0} + \sum_{i=1}^{N}\sum_{t=1}^{T_i}\mathbf{x}_{\mathbf{it}}\tilde{s}_{it}/\tilde{\sigma}^2_{SOW}\right], \left[\boldsymbol{\Sigma_0}^{-1} + \sum_{i=1}^{N}\sum_{t=1}^{T_i}\mathbf{x}_{\mathbf{it}}\mathbf{x}'_{\mathbf{it}}/\tilde{\sigma}^2_{SOW}\right]^{-1}\right) \tag{A14}$$
where β_0 and Σ_0 represent the respective prior mean and covariance of β.

Step 6: Update the γ coefficients corresponding to the instruments for endogenous FTF variable

a. Define $\tilde{f}_{it}$ as:
$$\tilde{f}_{it} = FTF_{it} - \begin{bmatrix}\sigma_{SOW,FTF} & \sigma_{FTF,PH} & \sigma_{FTF,EML}\end{bmatrix} \times \begin{bmatrix}\sigma_{SOW,SOW} & \sigma_{SOW,PH} & \sigma_{SOW,EML} \\ \sigma_{SOW,PH} & \sigma_{PH,PH} & \sigma_{PH,EML} \\ \sigma_{SOW,EML} & \sigma_{PH,EML} & \sigma_{EML,EML}\end{bmatrix}^{-1} \times \begin{bmatrix} SOW_{it*} - \alpha_i - \mathbf{x}'_{\mathbf{it}}\boldsymbol{\beta} \\ PH_{it} - \mathbf{z}'_{\mathbf{it,PH}}\boldsymbol{\gamma}_{\mathbf{PH}} \\ EML_{it} - \mathbf{z}'_{\mathbf{it,EML}}\boldsymbol{\gamma}_{\mathbf{EML}}\end{bmatrix} \tag{A15}$$

b. Define $\tilde{\sigma}^2_{FTF}$ as:

$$\tilde{\sigma}^2_{FTF} = \sigma_{FTF,FTF} - \begin{bmatrix} \sigma_{SOW,FTF} & \sigma_{FTF,PH} & \sigma_{FTF,EML} \end{bmatrix} \times \begin{bmatrix} \sigma_{SOW,SOW} & \sigma_{SOW,PH} & \sigma_{SOW,EML} \\ \sigma_{SOW,PH} & \sigma_{PH,PH} & \sigma_{PH,EML} \\ \sigma_{SOW,EML} & \sigma_{PH,EML} & \sigma_{EML,EML} \end{bmatrix}^{-1} \times \begin{bmatrix} \sigma_{SOW,FTF} \\ \sigma_{FTF,PH} \\ \sigma_{FTF,EML} \end{bmatrix} \quad \text{(A16)}$$

c. Define the two dimensional vector of instrument covariates as $\mathbf{z_{it,FTF}} = \begin{bmatrix} 1 & \text{PeerFTF}_{it} \end{bmatrix}'$, where PeerFTF_{it} is peer-based instrument as defined as in Appendix 1, and define the associated parameter vector of instruments as $\boldsymbol{\gamma}_{\mathbf{FTF}} = \begin{bmatrix} \gamma_{0,FTF} & \gamma_{1,FTF} \end{bmatrix}'$. (A17)

d. Draw $\gamma_{\mathbf{FTF}}$ as multivariate normal with the following mean and covariance:

$$\boldsymbol{\gamma}_{\mathbf{FTF}} \sim \text{MVN}\left(\left[\left(\boldsymbol{\Omega}_{\mathbf{0,FTF}}\right)^{-1} + \frac{\sum_{i=1}^{N}\sum_{t=1}^{T_i} \mathbf{z_{it,FTF}} \mathbf{z'_{it,FTF}}}{\tilde{\sigma}^2_{FTF}} \right]^{-1} \times \left[\left(\boldsymbol{\Omega}_{\mathbf{0,FTF}}\right)^{-1} \boldsymbol{\Gamma}_{\mathbf{0,FTF}} + \frac{\sum_{i=1}^{N}\sum_{t=1}^{T_i} \mathbf{z_{it,FTF}} \tilde{f}_{it}}{\tilde{\sigma}^2_{FTF}} \right], \left[\left(\boldsymbol{\Omega}_{\mathbf{0,FTF}}\right)^{-1} + \frac{\sum_{i=1}^{N}\sum_{t=1}^{T_i} \mathbf{z_{it,FTF}} \mathbf{z'_{it,FTF}}}{\tilde{\sigma}^2_{FTF}} \right]^{-1} \right)$$

(A18)

where $\Gamma_{\mathbf{0,FTF}}$ and $\Omega_{\mathbf{0,FTF}}$ represent, respectively, the prior mean and covariance of $\gamma_{\mathbf{FTF}}$. By repeatedly using the conditional distributional properties of the multivariate normal distribution and the appropriate instruments, the parameter estimates corresponding to the instruments for PH ($\gamma_{\mathbf{PH}}$) and EML ($\gamma_{\mathbf{EML}}$) can be updated in the same way.

Step 7: Update covariance matrix Σ

a. Define the 4×1 vector of residuals $\boldsymbol{\varepsilon}_{\mathbf{it}}$ as:

$$\boldsymbol{\varepsilon}_{\mathbf{it}} = \begin{bmatrix} \text{SOW}_{it*} - \alpha_i - \mathbf{x'_{it}}\boldsymbol{\beta} \\ \text{FTF}_{it} - \mathbf{z'_{it,FTF}}\boldsymbol{\gamma}_{\mathbf{FTF}} \\ \text{PH}_{it} - \mathbf{z'_{it,PH}}\boldsymbol{\gamma}_{\mathbf{PH}} \\ \text{EML}_{it} - \mathbf{z'_{it,EML}}\boldsymbol{\gamma}_{\mathbf{EML}} \end{bmatrix} \quad \text{(A19)}$$

b. Draw covariance Σ ~ Inverse-Wishart:

$$\boldsymbol{\Sigma} \sim \text{IW}\left(\nu_0 + K, \left[S_0 + \sum_{i=1}^{N}\sum_{t=1}^{T_i} \boldsymbol{\varepsilon}_{\mathbf{it}} \boldsymbol{\varepsilon}'_{\mathbf{it}} \right]^{-1} \right) \quad \text{(A20)}$$

where K denotes the entire sample size $K=\sum_{i=1}^{N}\sum_{t=1}^{T_i} 1$, ν_0 denotes the prior degrees of freedom parameter, and $\mathbf{S_0}$ denotes the prior scale matrix.

Step 8: Update population mean parameter μ, corresponding to the distribution of α_i

a. Define the prior for $\mu \sim N(\mu_0, \gamma_0^2)$

b. Draw $\mu \sim \text{univariate normal}\left(\dfrac{N\bar{\alpha}/\tau^2+\mu_0/\gamma_0^2}{N/\tau^2+1/\gamma_0^2},\ \left[N/\tau^2+1/\gamma_0^2\right]^{-1}\right)$ (A21)

where N denotes the total number of customers in the sample, and $\bar{\alpha}$ is the sample mean of α_i across all customers: $\bar{\alpha} = \dfrac{1}{N}\sum_{i=1}^{N}\alpha_i$ (A22)

Step 9: Update population variance parameter τ^2, corresponding to the distribution of α_i

a. Define the prior for $\tau^2 \sim \text{Inverse Gamma}(\eta_0/2, \eta_0\tau_0^2/2)$

b. Draw $\tau^2 \sim \text{Inverse Gamma}\left(\dfrac{\eta_0+N}{2},\ \dfrac{\eta_0\tau_0^2+\sum_{i=1}^{N}(\alpha_i-\mu)^2}{2}\right)$ (A23)

where N denotes the total number of customers in the sample.

This concludes the MCMC sampler.

Appendix 3

DETAILS FOR BREAKEVEN CALCULATIONS

We calculate breakeven points (number of months) at which communication channel synergies switch from being positive to negative (Figure 4 in the manuscript). Let $\beta_{a,b}$ represent the parameter estimate of the two-way interaction between two communication channels, a and b, and let $\beta_{o,a,b}$ represent the parameter estimate of the three-way interaction among the onboarding covariate $ONBOARD_{it}$, channel a, and channel b. Define ρ as:

$$\rho = \frac{\exp(\delta)}{1+\exp(\delta)}. \text{ Thus, per the manuscript, } ONBOARD_{it} = \rho^{(TIME-1)}. \tag{A24}$$

We use the posterior means for the δ and β coefficients, as estimated by our model, for the breakeven calculations. We are interested in solving for TIME where $\beta_{a,b} + \beta_{o,a,b} \times \rho^{(TIME-1)} = 0$. Recall that the effect of $\beta_{o,a,b}$ is temporary and decays to 0 over time at a rate of $\rho^{(TIME-1)}$. Thus, we would like to know the point in time at which the positive channel synergies of onboarding exactly offset the negative channel synergies not associated with onboarding. Taking the logs and solving explicitly for TIME yields the following breakeven level of communication channel synergy:

$$\text{Breakeven TIME} = 1 + \frac{\left[\mathrm{Ln}(-\beta_{a,b}) - \mathrm{Ln}(\beta_{o,a,b})\right]}{\mathrm{Ln}(\rho)} \tag{A25}$$

For example, the posterior mean for $\exp(\delta)/(1 + \exp(\delta)) = \rho = .81$. The posterior means for $\beta_{FTF \times PH}$ and $\beta_{Onboarding \times FTF \times PH}$ are, respectively, -.53 and 1.10. Inserting these values into Equation A25 yields:

$$\text{Breakeven TIME} = 1 + \frac{\left[\mathrm{Ln}(.53) - \mathrm{Ln}(1.10)\right]}{\mathrm{Ln}(.81)} = 4.5 \text{ months.} \tag{A26}$$

Similar methods apply to the breakeven calculations for the other channel synergies. Table A2 below presents the full set of parameter estimates used for calculating the breakeven quantities.

TABLE A2
Impact of Onboarding on Multichannel Interactions

Parameter estimates	Posterior means		95% Posterior intervals	
Face-to-face × telephone interaction				
Face-to-face × telephone	-.53	**	[-.74,	-.33]
Onboarding × face-to-face × telephone	1.10	**	[.74,	1.47]
Total net effect with onboarding benefits	.57	**	[.01,	1.14]
Face-to-face × email interaction				
Face-to-face × email	-.31	**	[-.34,	-.27]
Onboarding × face-to-face × email	.82	**	[.75,	.90]
Total net effect with onboarding benefits	.51	**	[.40,	.62]
Telephone × email interaction				
Telephone × email	-.32	**	[-.39,	-.25]
Onboarding × telephone × email	.64	**	[.51,	.78]
Total net effect with onboarding benefits	.32	**	[.12,	.53]

**More than 95% of the posterior distribution for the parameter estimate does not include zero.

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TABLE 1
Select Multichannel Research Relevant to Customer Onboarding

Sources	Communication Channels	Customer Relationship Duration	Functional Form	Multichannel Interactions	Onboarding Dynamics	Communication Carryover	Dependent Variables	Key Findings
Cannon and Homburg (2001)	1. Face-to-face 2. Telephone 3. Email/letter/fax	Various	Linear				Product acquisition costs, operations costs for buyer firms in the buyer-supplier dyad	More frequent FTF and email/letter/fax communication lowers operations costs for buyer firms; telephone communication does not. More frequent email/letter/fax communication lowers acquisition costs for buyer firms; telephone communication does not.
Godfrey, Seiders, and Voss (2011)	1. Telephone 2. Email 3. Direct mail	Not mentioned	Inverted-U	✓ (negative)			Repurchase visits, spending	In all channels, frequency has an inverted U-shaped relationship with repurchase visits and spending. The point at which the channel peaks is inversely related to richness, such that it is highest with mail, followed by email, then telephone. There are negative interaction effects for phone×email and email×direct mail; the phone×direct mail interaction is marginally negative on spending and not significant on repurchase visits.
Kozlenkova et al. (2017)	None (Bilateral communication on an e-commerce platform)	Restricted cohort (joined e-commerce platform after a certain start date)	Linear		✓ (negative interaction with time)		Buyer's relationship formation	The positive effect of bilateral communication on buyer's relationship formation gets smaller with the buyer's experience (i.e., time since the buyer joined the online shopping community).
Kumar, Venkatesan, and Reinartz (2008)	1. Web (customer-initiated) 2. Face-to-face 3. Telephone/direct mail	Not mentioned	Linear (web); Inverted-U (FTF; phone/mail)				B-to-B customer firm purchase timing (i.e., time between two purchases)	Web communication initiated by the customer firm to the supplier reduces the time between purchases (i.e., interpurchase timing). Frequency of FTF and telephone/direct mail communication has a U-shaped relationship with purchase timing. Overall, communication timed to coincide with the month in which customers are likely to purchase increases firm's profits and ROI.
Palmatier et al. (2013)	None (Bilateral communication capabilities)	Various	Linear		✓ (negative interaction with time)		Commitment velocity	The positive effect of bilateral communication capabilities on commitment velocity gets smaller as the relationship ages.
Reinartz, Thomas, and Kumar (2005)	1. Face-to-face 2. Telephone 3. Email 4. Web (customer-initiated)	Same cohort (made first purchase at the same time)	Linear	✓ (positive)			Customer acquisition, relationship duration, customer profitability	FTF, phone, and email communication increase customer acquisition, relationship duration, and profitability, with FTF having the biggest impact, followed by phone and email. Web communication is also positively related to all three outcomes. FTF×email and telephone×email interactions are positive for all dependent variables. The FTF×telephone interaction is not significant.
Venkatesan and Kumar (2004)	1. Face-to-face 2. Telephone/direct mail 3. Web (customer-initiated)	Two cohorts (each made first purchase at the same time)	Linear (web); Inverted-U (FTF; phone/mail)				Purchase frequency	Frequency of FTF and telephone/direct mail communication have an inverted U-shaped relationship with purchase frequency. The point at which the channel peaks is inversely related to richness, such that it is higher for telephone/direct mail than FTF communication. Customer-initiated web communication increases purchase frequency.
Zantedeschi, Feit, and Bradlow (2016)	1. Email 2. Catalog	Various	Linear	✓ (positive)		✓ (constant)	Customer purchases	E-mail and catalog have approximately the same overall effect on customer purchases, but catalogs have a longer-lasting (i.e., carryover) impact than emails. Email × catalog interaction is positive.
Our research	1. Face-to-face 2. Telephone 3. Email	Same cohort (started relationship at the same time)	Inverted-U	✓ (positive switching to negative based on time)	✓ (encoding and carryover)	✓ (time-varying)	Customer share of wallet	Every channel has a significantly greater main effect and carryover effect early in the customer relationship (onboarding encoding and carryover), and both are enhanced by channel richness. The multichannel interactions are positive early in the relationship (onboarding window), but switch to negative later on (post-onboarding window).

Notes: For communication channels, a slash (/) indicates the channels were combined into a single construct. Blank indicates that the effect was not modeled.

TABLE 2
Constructs / Effects, Definitions, and Operationalizations

Constructs / Effects	Definitions	Operationalizations
Multichannel communication	The number of communication contacts per channel per month for each customer	Communication frequency in each of the three channels: face-to-face, telephone, and email for each customer
Communication channel richness	"The ability of information to change understanding within a time interval" (Daft and Lengel 1986, p. 560).	The three communication channels in this research in decreasing order of richness, based on media richness theory, are: 1) face-to-face, 2) telephone, then 3) email
Onboarding Dynamic Effects		
Onboarding encoding (H_1)	The effect of communication (in any channel) on performance should be greatest at the beginning of the relationship and should get smaller as the relationship ages.	Interactions between each communication channel and the onboarding encoding effect, which vary as a function of time: Onboarding × face-to-face, Onboarding × phone, and Onboarding × email
Onboarding carryover (H_2)	The effect of communication (in any channel) will typically last more than one period (i.e., carryover). This carryover effect should be greatest at the beginning of the relationship and should get smaller as the relationship ages.	Carryover effects are modeled linearly as a function of time t, then constrained to lie in the interval (0,1) using the inverse logit transformation: $\kappa_t = \pi_0 - \exp(\pi_1)\times(t-1)$ $\lambda_t = \frac{\exp(\kappa_t)}{1+\exp(\kappa_t)}$ Specifically tests whether the coefficient for the linear time trend, $-\exp(\pi_1)$, is negative and statistically significant for each channel.
Onboarding Richness Effects		
Onboarding richness encoding (H_3)	The effect of onboarding encoding should be greater for richer versus leaner channels.	Examines differences across communication channels. Are interaction effects between each channel with onboarding encoding significantly different from each other: Onboarding × face-to-face - Onboarding × phone > 0 Onboarding × face-to-face - Onboarding × email > 0 Onboarding × phone - Onboarding × email > 0
Onboarding richness carryover (H_4)	The onboarding carryover effect should decay more slowly over the relationship for richer versus leaner channels.	Examine whether the differences in the estimated linear time trend coefficients for richer vs. leaner channels are positive and significant: $-\exp(\pi_{1,\text{face-to-face}}) - (-\exp(\pi_{1,\text{telephone}})) > 0$ $-\exp(\pi_{1,\text{face-to-face}}) - (-\exp(\pi_{1,\text{email}})) > 0$ $-\exp(\pi_{1,\text{telephone}}) - (-\exp(\pi_{1,\text{email}})) > 0$
Dependent Variable		
Customer share of wallet	The total proportion of the customer's financial assets allocated to the focal firm.	Customer's total assets (deposits + investments) with the focal firm, divided by customer's total assets across all financial institutions (total asset wallet)
Control Variables		
Lagged SOW	Lagged (one month) customer share of wallet	$SOW_{i(t-1)}$. Helps control for SOW stickiness (inertia effects over time)
Total transactions	Total customer servicing transactions (monthly)	Sum of all transactions by customer in current time period (month)
Log (total loan balances)	Total loan balances, which represent the total debts the customer owes to the focal firm	Log of total loan balances, measured monthly
Total number of accounts	Total number of accounts owned by customer	Sum of all open accounts owned by customer in current time period (month)
Mobile banking user	Customer status for mobile banking	Dummy variable; 1 = customer has downloaded the mobile banking application; 0 = otherwise
Customer age	Customer's age	Customer's age in years

TABLE 3
Descriptive Statistics and Correlations

	Variables	M	SD	1	2	3	4	5	6	7	8
1	Customer share of wallet	6.96	21.52								
2	Face-to-face communication frequency	1.83	3.94	.10							
3	Telephone communication frequency	.54	1.45	.04	.10						
4	Email communication frequency	9.80	16.04	.09	.12	.09					
5	Total transactions	11.05	23.90	.23	.24	.15	.25				
6	Log of total loan balances	4.31	4.70	-.21	-.15	-.06	-.11	-.32			
7	Total number of accounts	1.48	.91	.31	.22	.10	.26	.46	-.20		
8	Mobile banking user	.43	.49	.14	.11	.08	.37	.36	-.26	.34	
9	Customer age	43.79	15.91	-.05	-.08	-.05	-.17	-.23	.10	-.15	-.34

Notes: All correlations are significant at $p < .01$.

TABLE 4
Results: Multichannel Customer Onboarding

Parameter estimates	Hypotheses	Posterior means		95% Posterior intervals	
Intercept		-35.90	**	[-36.36,	-35.43]
Known Communication Effects					
Current communication richness					
Face-to-face		2.98	**	[2.76,	3.21]
Telephone		.01		[-.32,	.35]
Email		1.80	**	[1.72,	1.89]
Multichannel inverted-U					
$(\text{Face-to-face})^2$		-.18	**	[-.21,	-.14]
$(\text{Telephone})^2$		-.13	**	[-.21,	-.05]
$(\text{Email})^2$		.00		[.00,	.01]
Multichannel interaction					
Face-to-face × telephone		-.12		[-.27,	.03]
Face-to-face × email		-.07	**	[-.10,	-.04]
Telephone × email		-.13	**	[-.19,	-.07]
Face-to-face - telephone		2.97	**	[2.55,	3.41]
Face-to-face - email		1.18	**	[.94,	1.41]
Telephone - email		-1.79		[-2.13,	-1.43]
Past communication richness					
Stock face-to-face		.48	**	[.46,	.52]
Stock telephone		.32	**	[.26,	.38]
Stock email		.12	**	[.11,	.13]
Stock face-to-face - stock telephone		.17	**	[.09,	.23]
Stock face-to-face - stock email		.37	**	[.34,	.40]
Stock telephone - stock email		.20	**	[.14,	.26]
Onboarding Dynamic Effects					
Onboarding encoding					
Onboarding decay parameter δ		.81	**	[.81,	.82]
Onboarding		9.89	**	[9.72,	10.07]
Onboarding × face-to-face	$\mathbf{H_{1a}}$	3.02	**	[2.82,	3.22]
Onboarding × telephone	$\mathbf{H_{1b}}$	2.69	**	[2.30,	3.08]
Onboarding × email	$\mathbf{H_{1c}}$	1.11	**	[1.03,	1.19]
Onboarding carryover					
$-\exp(\pi_{1,\text{face-to-face}})$	$\mathbf{H_{2a}}$	-.28	**	[-.36,	-.21]
$-\exp(\pi_{1,\text{telephone}})$	$\mathbf{H_{2b}}$	-3.26	**	[-3.46,	-3.09]
$-\exp(\pi_{1,\text{email}})$	$\mathbf{H_{2c}}$	-1.55	**	[-1.69,	-1.33]
Onboarding Richness Effects					
Onboarding richness encoding					
Onboarding × face-to-face - onboarding × phone	$\mathbf{H_{3a}}$	.33		[-.12,	.77]
Onboarding × face-to-face - onboarding × email	$\mathbf{H_{3b}}$	1.91	**	[1.69,	2.13]
Onboarding × phone - onboarding × email	$\mathbf{H_{3c}}$	1.58	**	[1.17,	1.99]
Onboarding richness carryover					
$-\exp(\pi_{1,\text{face-to-face}}) + \exp(\pi_{1,\text{telephone}})$	$\mathbf{H_{4a}}$	2.98	**	[2.78,	3.23]
$-\exp(\pi_{1,\text{face-to-face}}) + \exp(\pi_{1,\text{email}})$	$\mathbf{H_{4b}}$	1.29	**	[1.06,	1.46]
$-\exp(\pi_{1,\text{telephone}}) + \exp(\pi_{1,\text{email}})$	$\mathbf{H_{4c}}$	-1.74		[-2.00,	-1.47]

**More than 95% of the posterior distribution for the parameter estimate does not include zero, and the results are also consistent with direction of proposed hypotheses (where applicable).

FIGURE 1
Multichannel Customer Onboarding

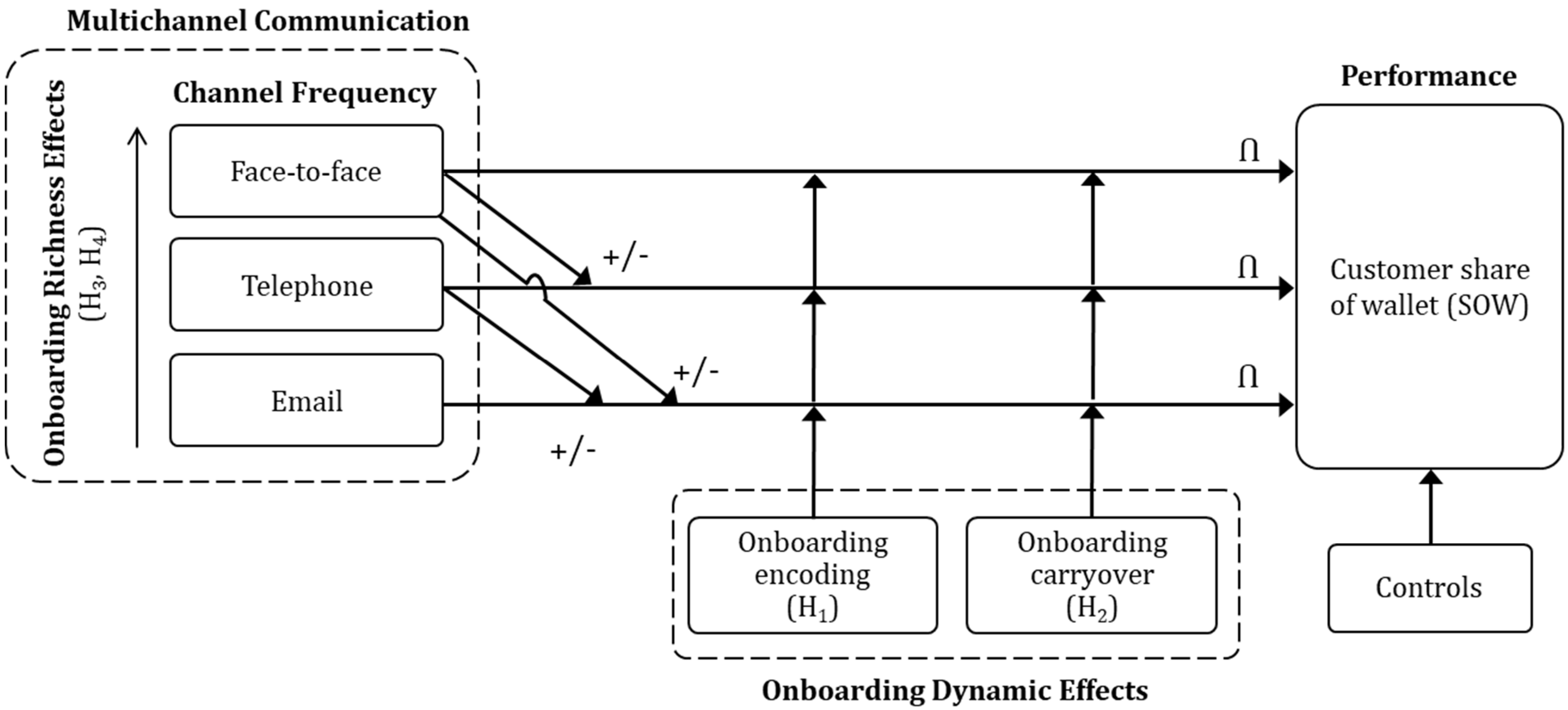
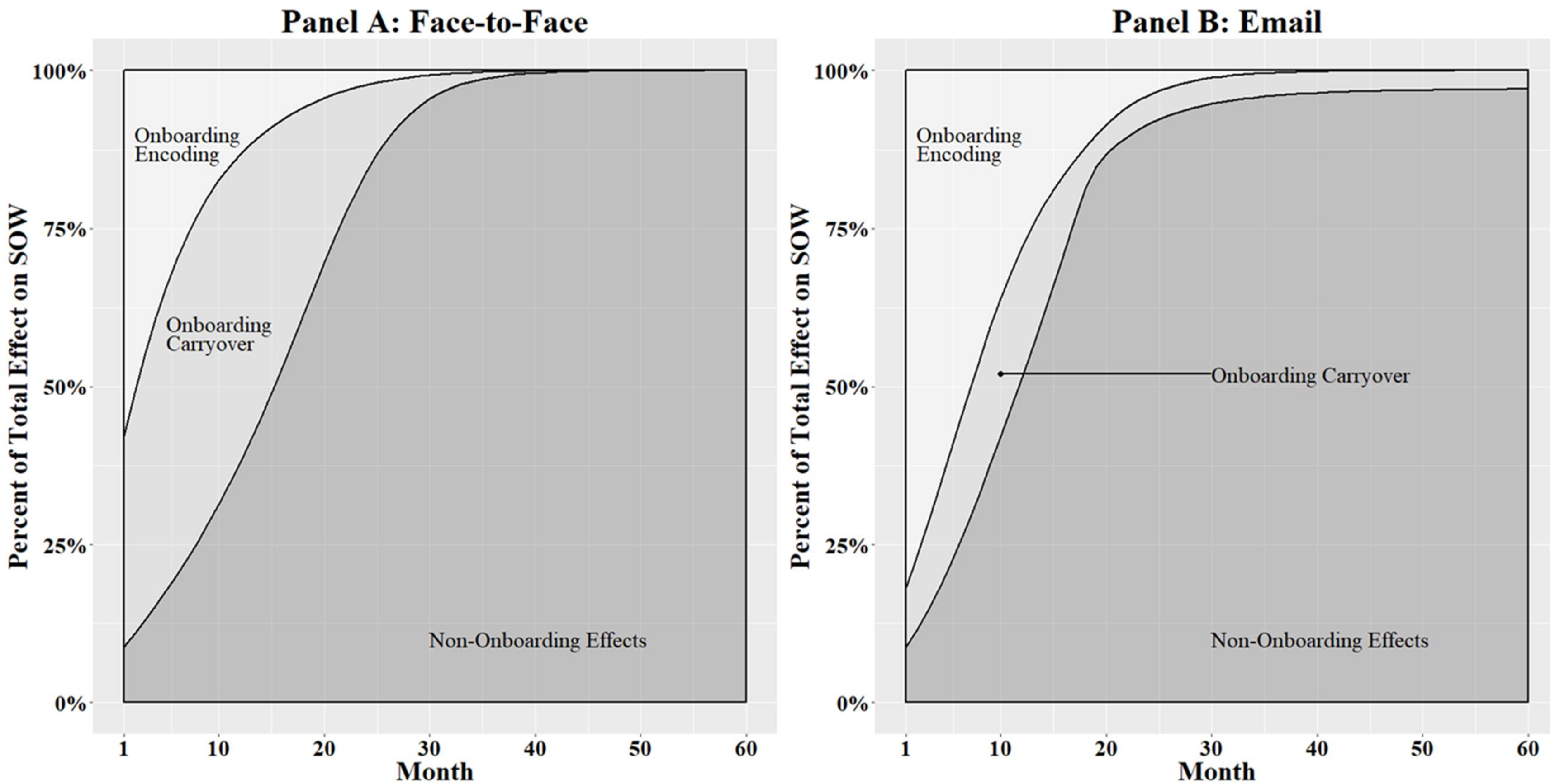
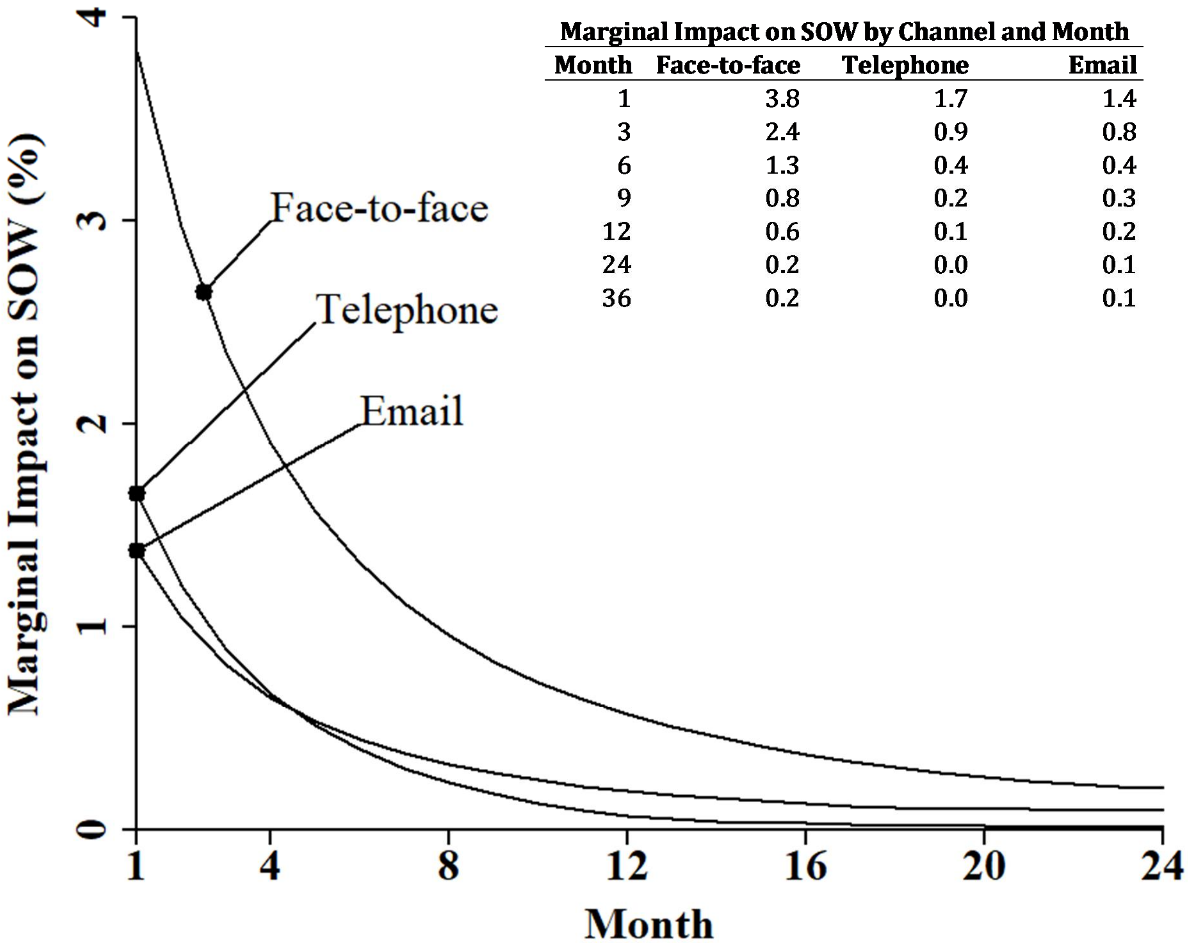


FIGURE 2
Customer Onboarding: Decomposition, Magnitude, and Duration of Effects



Notes: Each plot decomposes the total effect of one additional communication by channel into 1) non-onboarding (permanent) effect, 2) onboarding encoding effect, and 3) onboarding carryover effect. The area chart sums to 100% and illustrates the relative importance of each one of these three effects on changes to SOW for the average customer in our sample as a function of time. Because the permanent effect of telephone was not significantly different from 0, we only plot the comparisons between face-to-face (richest channel) and email (leanest channel).

FIGURE 3
Relationship Effectiveness of Communication Richness Strategies

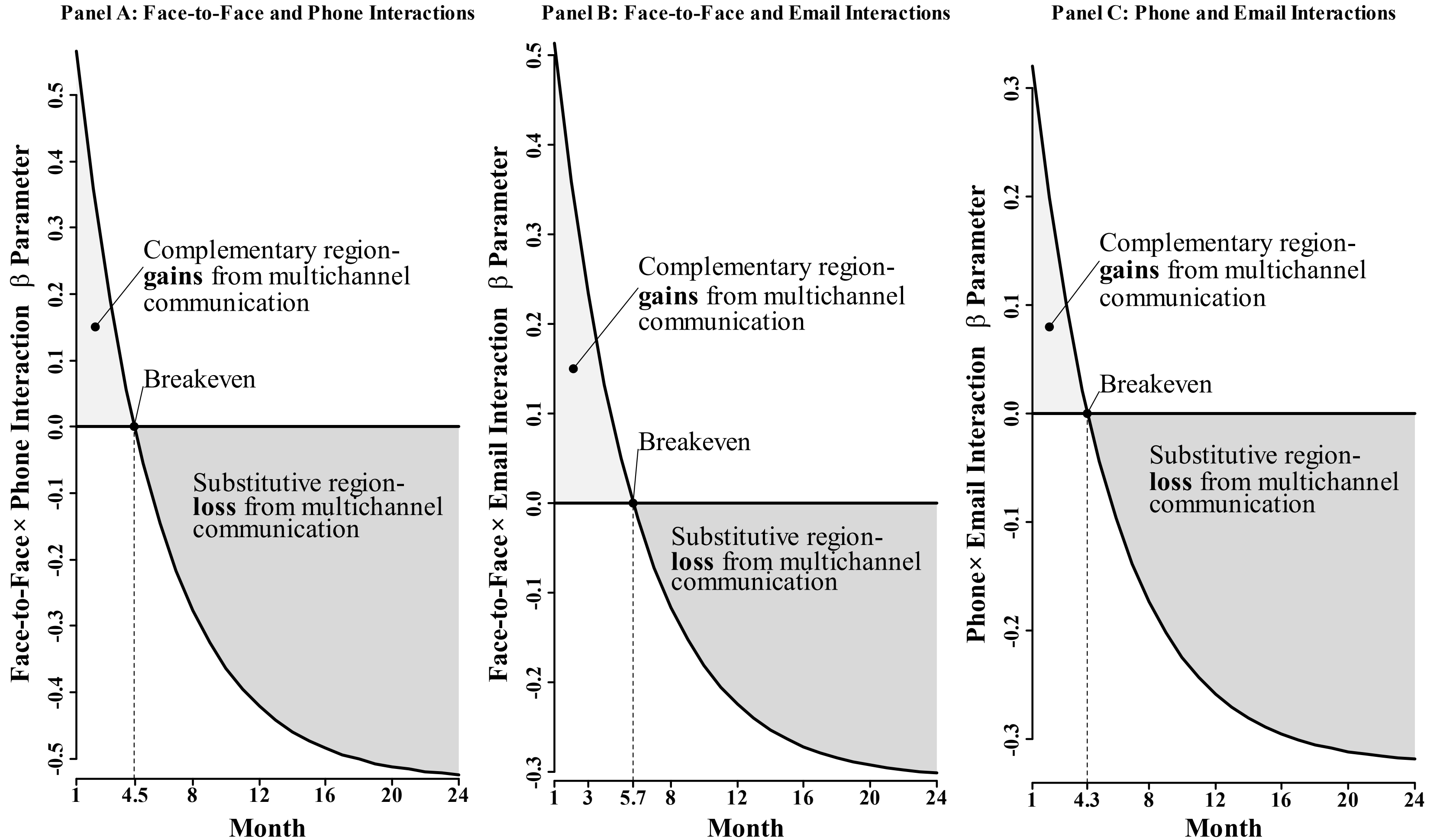


Marginal Impact on SOW by Channel and Month

Month	Face-to-face	Telephone	Email
1	3.8	1.7	1.4
3	2.4	0.9	0.8
6	1.3	0.4	0.4
9	0.8	0.2	0.3
12	0.6	0.1	0.2
24	0.2	0.0	0.1
36	0.2	0.0	0.1

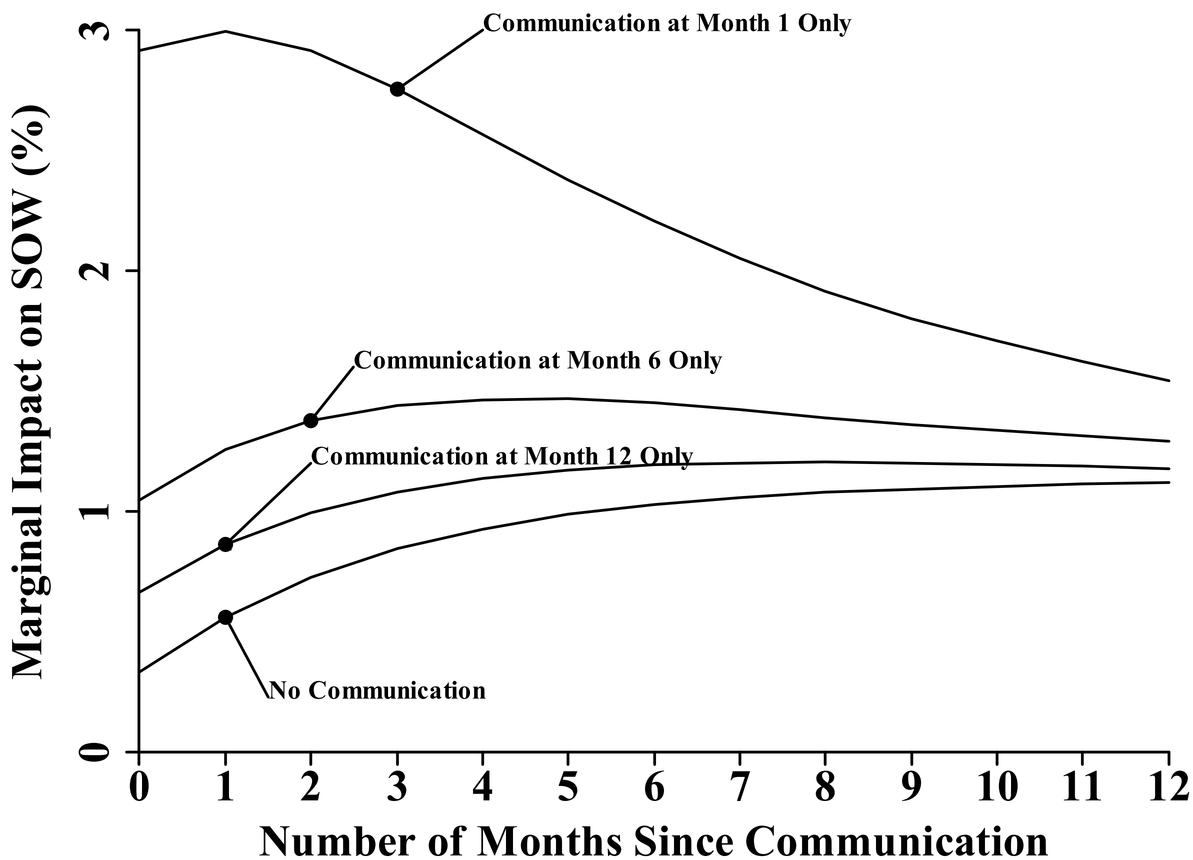
Notes: Plot shows the total net impact of one additional face-to-face, telephone, and email communication on SOW by month for the first two years. Plot includes the sum of permanent, first impressions and onboarding carryover effects. The table shows select values for actual changes to SOW for one additional communication over time. For example, one additional face-to-face communication is expected to increase SOW by 3.8% in Month 1, but only by .2% in Month 24. Results demonstrate that richer works better earlier, as the incremental impact of face-to-face communication over other channels is much larger early on (larger vertical distance).

FIGURE 4
Onboarding Insights to Multichannel Complementarity versus Substitutive Interaction Effects



Notes: This figure illustrates how quickly the positive benefits of communication channel interactions decrease as a function of time. All channel interactions start out positive (complementary effects) but become negative (substitutive effects) as onboarding benefits expire. Because interactions are positive for only about the first four to six months, the region of losses (substitutive effects) is larger; most customer relationships last longer than six months in our sample.

FIGURE 5
Impact of Single-Period Communications on Future Performance Trajectories



Notes: Plot shows the collective total impact of one additional FTF, telephone, and email communication on current SOW as well as on future SOW for up to 12 months into the future, for the average customer in our sample. The average customer's trajectory is also plotted for no communication so comparisons can be made. Plot illustrates that early communication has a profound impact on both a customer's current and future relational trajectories. For example, communication at Month 1 still has a significant effect on the customer's relationship 12 months later; however the same communication occurring at Month 12 has almost no effect 12 months later, when compared to the baseline.