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RESEARCH ARTICLE

HOW DO ADOPTERS TRANSITION BETWEEN NEW AND INCUMBENT CHANNELS?[1]

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There is substantial knowledge about how individuals and organizations, which we refer to collectively as entities, adopt and use new channels. However, less is known about how this relates to their use of the incumbent channel that the new channel may replace. To address this gap, we examine how entities transition between incumbent and new channels over time, with a particular focus on two temporal factors: when an entity adopts the new channel and how long an entity has used the channels, which we refer to as the entity's channel history. Our results show that entities that adopt at similar times often follow dramatically different patterns of new and incumbent channel use. This allows us to expand upon the traditional adopter categories of innovators, early adopters, early majority, late majority, and laggards. We also find that an entity's channel history influences how it transitions between the incumbent and new channels, and we document other factors that influence these transitions. Our results contribute to theory about the adoption/diffusion of new channels, and they contribute to practice by giving managers tools to understand and predict how entities' use of new and incumbent channels evolves over time.

Keywords: New channel, incumbent channel, diffusion, adoption, adopter categorization, channel history, heterogeneity, dynamics, automotive, pro-innovation bias

Introduction

When an individual or organization, which we refer to collectively as entities, adopts a new channel, do they continue to use the incumbent channel? For example, after an entity adopts a mobile shopping app (i.e., the new channel), do they continue to purchase at physical stores (i.e., the incumbent channel)? Or, after an entity adopts online distance education or telemedicine, do they continue to use traditional classrooms or physical medical clinics? We have substantial knowledge of how entities adopt and use new channels, with this understanding spanning multiple domains such as retail, education, and medicine (e.g., Bernard et al. 2004; Heffner et al. 2009; Miscione 2007; Neslin and Shankar 2009; Wootton 2012). However, we know less about how use of a new channel relates to use of the incumbent channel that predates it, particularly how this varies across adopting entities and over time. For example, some entities that adopt the new channel might gradually phase out their use of the incumbent channel, while others may forsake it immediately. Some may use both channels indefinitely, while others may scale back or discontinue their use of the new channel. We address this gap by analyzing how and why entities transition between new and incumbent channels over time, focusing on two temporal

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factors: when an entity adopts the new channel and how long an entity has used the channels.[2]

As part of our analysis of *how* entities use new channels *vis-à-vis* incumbent channels over time, we derive a typology of channel use patterns and review the literature on each pattern. The typology makes clear that entities that adopt a new channel at similar times often follow dramatically different post-adoption channel use patterns. Some continue to use the incumbent channel along with the new channel (following what we refer to as an extension pattern), some abruptly abandon the incumbent (abrupt replacement), some adopt the new channel but revert back to the incumbent (discontinuance), etc. We validate this empirically by analyzing over 50,000,000 transactions that reflect how used car dealers used a new electronic purchasing channel and the incumbent physical purchasing channel over a 6.25 year span. This allows us to expand upon the traditional adopter categories of innovators, early adopters, early majority, late majority, and laggards (Rogers 2003). For example, we show that some innovators (and early adopters) are extenders, others are replacers, and others are discontinuers.

To analyze *why* the use of a new channel *vis-à-vis* an incumbent channel differs across entities and over time, we examine factors that affect entities' transitions between channels. We focus on the role of an entity's channel history, which is how long it has used the channels. Prior literature is unclear on how channel history will influence entities' transitions between new and incumbent channels. On one hand, entities with a long channel history may have established routines/habits of using the incumbent channel that impede their transition to the new channel (Polites and Karahanna 2013). On the other hand, entities with a long channel history might be uniquely positioned to understand the benefits of the new channel *vis-à-vis* the incumbent channel, thereby causing them to quickly transition to the new channel (Valentini et al. 2011). A consideration of both perspectives yields a nuanced view in which entities with long channel histories may have a similar likelihood as those with short channel histories to transition to using the new channel (in order to capture the expected benefits), but a higher likelihood to continue using the incumbent channel at the same time (given the force of habit). In other words, entities with long channel histories are more likely to follow an extension pattern, while entities with short channel histories are more likely to follow a replacement pattern. We find support for this nuanced effect in our empirical context. We also identify and test several other variables that influence how entities transition between new and incumbent channels, including the fit of each channel to their needs, the transaction costs of using each channel, the channel use patterns of their neighbors, and the frequency with which they engage in the functions that the channels provide.

By studying how and why adopters transition between new and incumbent channels over time, we contribute to the literature on the post-adoption use of innovations. Because the pace of innovation diffusion continues to accelerate (Downes and Nunes 2013; Van den Bulte 2000), thereby compressing the distinctions between the traditional adopter categories, understanding what happens post-adoption is increasingly important relative to understanding when an entity adopts. We show that adopters are not only innovators, early adopters, etc.; they are also extenders, replacers, etc. (and we examine why). This helps address the pro-innovation bias of the innovation diffusion literature (Sveiby et al. 2012), a symptom of which is that the literature has focused heavily on an innovation's diffusion with little regard to what happens afterward, including how use of the innovation relates to use of the incumbent practice/technology/channel that the innovation might replace. Our findings also have practical value to managers tasked with introducing new channels and supporting incumbent channels. Understanding how and why adopters use the channels can help managers measure the success of the new channel and determine whether to continue investment in the incumbent channel.

Literature Review and Typology of Channel Use Patterns

We examine how entities' use of a new channel relates to their use of the incumbent channel, including how this evolves over time. Drawing on the marketing literature (e.g., Kotler and Keller 2016), we define *channel* as a mechanism through which a product, a service, and/or information is delivered. For example, a physical store and a mobile shopping app are both channels because they are mechanisms through which customers acquire products, services, and/or information. When comparing two channels that serve similar functions, the one that was introduced first is the *incumbent channel*. In the example above, the physical store is the incumbent channel and the mobile shopping app is the new channel. Other examples include doctors' offices (incumbent channel) and telemedicine systems (new channel), physical classrooms (incumbent) and distance education systems

[2] *Entity* is synonymous with *population unit*. If the population under study consists of organizations, then an entity is an organization. If the population consists of individuals, then an entity is an individual. We use the term entity to be fully general, as our discussion is not specific to either the organizational or individual level.

(new), and dating web sites (incumbent) and dating mobile apps (new). Several studies compare physical and electronic channels (as we do in our empirical analysis); in these studies, the electronic channel is typically the new channel, although this need not always be the case. It is also possible to compare new and incumbent electronic channels (or new and incumbent physical channels), as the dating web sites/dating apps example above illustrates.

Our analysis contributes to three main areas. First, our analysis helps us address the pro-innovation bias of the innovation diffusion literature. Second, it contributes to research on the use of innovations after adoption. Third, it contributes to research on how entities use new and incumbent channels in conjunction with or instead of each other. As part of our discussion of the third area, we derive the typology of channel use patterns.

Pro-innovation Bias

A long-standing critique of the technology adoption and innovation diffusion literature is its implicit pro-innovation bias. The pro-innovation bias is the "implication in diffusion research that an innovation should be diffused and adopted"; it is "one of the most serious shortcomings of diffusion research" (Rogers 2003, p. 106). Studies that exhibit pro-innovation bias assume that innovations are beneficial, such that successful adoption is the desired goal. One consequence of the pro-innovation bias is that we know more about initial adoption than post-adoption use behaviors such as discontinuance. A related consequence is that we know relatively little about how adoption of an innovation affects the incumbent practice/technology/channel that it might replace. Rogers (2003, p. 115) laments this situation, stating that "researchers should investigate the broader context in which an innovation diffuses, such as … how the innovation of study is related to other innovations and to the existing practice(s) that it replaces." The pro-innovation bias persists (Greenhalgh et al. 2010; Jeyaraj et al. 2006; Joseph 2010; Sveiby et al. 2012), although progress is being made. For example, innovations can be "disappointing" (Greve 2011). Also, measurement challenges that have historically compounded the bias (Fichman 2004) are no longer as constraining as they once were. Better data are becoming available to permit investigation of longitudinal use and possible discontinuance of innovations at an entity level. For example, individual usage logs from an enterprise collaboration system (Fisher et al. 2018) show how different factors affect system adoption (e.g., a supervisor's use) and discontinuance (e.g., peer use).

Initial Adoption and On-Going Use

Much of the adoption/diffusion literature focuses on initial adoption of a product such as a television, refrigerator, or mobile phone. These studies are common because they are of interest to entities who sell or support the products and because data are often available on new product purchases. By contrast, data on continued use of product innovations, including whether an entity abandons an innovation and returns to a previous practice, are often unavailable. This highlights the importance of studying not only adoption but also use (e.g., Devaraj and Kohli 2003). Several studies, particularly those that focus on new information systems, measure use of an innovation as well its adoption (e.g., Sykes and Venkatesh 2017; Venkatesh et al. 2012). Studying post-adoption use is increasingly important as the speed of innovation diffusion increases (Downes and Nunes 2013; Van den Bulte 2000), thereby compressing the distinctions between traditional adopter categories. This makes analyzing what happens post-adoption increasingly important compared to studying when an entity adopts. We contribute to this line of research by studying not only use of the innovation but also how this use relates to use of the incumbent practice/technology/channel that it might replace. Exploring this may not be relevant in some contexts, such as when an organization adopts a new information system and shuts down the previous one, thereby requiring use of the new. However, how use of the innovation relates to use of the incumbent is relevant in cases in which the incumbent remains viable. This is often true of channels, such as those for purchasing, receiving medical care, interacting with friends, receiving education, etc. Indeed, the incumbent channels in these contexts (e.g., physical stores/clinics/schools) remain robust, and it is relatively easy for adopters of a new channel to also use the incumbent channel or to revert back to it completely. This may also be true in cases in which using a new organizational information system is voluntary.

Entities' Use of New and Incumbent Channels

Despite the prevalence of pro-innovation bias, prior research has examined how entities' use of a new channel relates to their use of the incumbent channel. One key stream is whether the new channel substitutes for or complements the incumbent channel (e.g., Herhausen et al. 2015; Oberholzer-Gee and Strumpf 2007). Another stream examines how status quo bias, switching costs, and habit can cause entities to continue using the incumbent channel even if fully embracing the new would be optimal (e.g., Polites and Karahanna 2013; Samuelson and Zeckhauser 1988). Much of the research in this stream proposes interventions designed to encourage entities to abandon use of the incumbent in favor of the new (e.g., Langer et al. 2012, Polites and Karahanna 2013). This is a manifestation of the pro-innovation bias, because it implies that the new channel (or new technology in a more general sense) should supplant the incumbent, at least to some degree. This implication is reflected in article titles such as "*Shackled* to the Status Quo" (Polites and Karahanna 2012; emphasis added) and "*Ushering* Buyers into Electronic Channels" (Langer et al. 2012; emphasis added).

We examine the different ways that entities might use a new channel *vis-à-vis* the incumbent channel after adopting the new. For example, some entities may rapidly replace the incumbent channel after adopting the new, others may use both channels indefinitely, and others may revert back to their use of the incumbent. Below, we derive a typology of these use patterns and comment on prior research related to each.

Derivation of the Typology

Consider entity i's use of a new and incumbent channel over multiple time periods t. In each period t, entity i is in one of multiple states of new *vis-à-vis* incumbent use. If entity i uses only the incumbent channel, then it is in the "incumbent" state. If entity i uses only the new channel, then it is in the "new" state. If entity i uses both channels, then it is in the "both" state. To derive the typology, we examine three periods and three states: incumbent, both, and new. We use three periods because it matches the three states; this allows an entity to transition through each of the states in the overall time span. In the appendix, we discuss the implications of altering the parameters (e.g., the number of periods and/or states) used to derive the typology.

We assume that entities are in the incumbent state in the first period. In the second and third periods, entities may transition to (or remain in) the incumbent, both, or new states. To capture all combinations, we permute the three states across the second and third periods. This yields nine permutations, each of which represents a channel use pattern. Table 1 shows these patterns, including graphical depictions of each. Placing entities in the incumbent state in the first period means that the patterns in the typology apply to entities who used the incumbent channel prior to their adoption of the new channel. In the appendix, we consider cases in which entities' initial use of both channels occurs simultaneously (i.e., who are in the both state in the first period) and entities who begin use of the new channel without having previously used the incumbent channel (i.e., who are in the new state in the first period).[3]

Extension: The *extension* pattern reflects entities that transition from using only the incumbent channel to using both channels (see the Inc→Inc→Both and Inc→Both→Both patterns in Table 1). This pattern is well-established in the literature. In a general sense (i.e., not specific to channels), the extension pattern is evident any time an adopter of an innovation continues to use the incumbent technology/channel/etc. One example of such behavior occurs when adopters of a new organizational information system continue to use the incumbent system in parallel (e.g., Bala and Venkatesh 2016; Robey et al. 2002). Another example occurs when an adopter of a new platform continues to use an incumbent platform, that is, when the adopter "multi-homes" (Rochet and Tirole 2003).

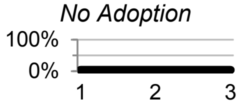
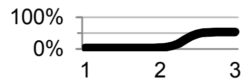
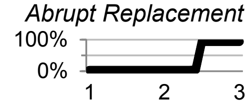
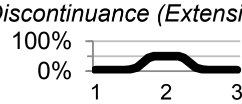
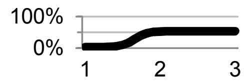
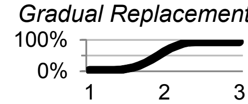
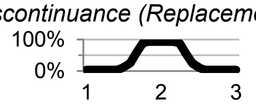
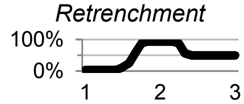
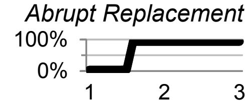
Much of the research on the extension pattern that is specific to channel use comes from the economics, marketing, and information systems literatures. Several studies have examined whether new channels are complementary/supplemental to incumbent channels; in other words, whether adopters of a new channel engage in an extension pattern in which they use both channels. For example, research has found complementarity between mobile apps and mobile web sites (Xu et al. 2014) and that electronic retail channels supplement, rather than substitute for, physical channels (Biyalogorsky and Naik 2003).

Replacement (Gradual and Abrupt): The *gradual replacement* and *abrupt replacement* patterns reflect entities that transition from using only the incumbent channel to using only the new channel. The difference between the two is how quickly this transition occurs. *Gradual replacement* reflects entities that transition from using only the incumbent channel to using both channels to using only the new channel (see the Inc→Both→New pattern in Table 1). *Abrupt replacement* reflects entities that shift directly from using only the incumbent channel to using only the new channel (see the Inc→Inc→New and Inc→New→New patterns in Table 1, the difference between which is simply when the entity adopts the new channel). In other words, there is no transitional period in which these entities use both channels.

These two patterns have long been recognized and are documented in Rogers' (2003) comprehensive account of innovation diffusion, although not necessarily for channel use specifically. Some of the first innovation diffusion studies, including those on farmers' adoption of agricultural innovations such as hybrid seed corn (e.g., Ryan and Gross 1943), found that adopters used an innovation on an experimental basis (alongside the incumbent practice) before transitioning fully

[3]By definition, the distinction between the incumbent and new channels is that the incumbent was introduced before the new. This does not mean that entities must use the incumbent channel first; it means only that the incumbent channel was introduced first. For example, a young person making his/her first clothing purchase might do so via a mobile shopping app (new channel) instead of at a physical store (incumbent channel).

Table 1. Typology of New and Incumbent Channel Use Patterns

<table>
<tr><th colspan="2"></th><th colspan="3">State at Period 3</th></tr>
<tr><th colspan="2"></th><th>Inc: Incumbent Channel Only</th><th>Both: Both Channels</th><th>New: New Channel Only</th></tr>
<tr><td rowspan="3">State at Period 2</td><td>Inc: Incumbent Channel Only</td><td>Inc→Inc→Inc
No Adoption
</td><td>Inc→Inc→Both
Extension
</td><td>Inc→Inc→New
Abrupt Replacement
</td></tr>
<tr><td>Both: Both Channels</td><td>Inc→Both→Inc
Discontinuance (Extension)
</td><td>Inc→Both→Both
Extension
</td><td>Inc→Both→New
Gradual Replacement
</td></tr>
<tr><td>New: New Channel Only</td><td>Inc→New→Inc
Discontinuance (Replacement)
</td><td>Inc→New→Both
Retrenchment
</td><td>Inc→New→New
Abrupt Replacement
</td></tr>
</table>

Notes: The matrix represents the typology of new and incumbent channel use patterns, as derived from a permutation of three states over periods 2 and 3 in which the state in period 1 is "Inc: Incumbent Channel Only." In the graphical depictions of each pattern, the x-axis represents time and the y-axis denotes the entity's state, depicted as the entity's percentage of new channel use relative to total use (i.e., new + incumbent use).

to the innovation. This reflects gradual replacement. Rogers notes other studies (e.g., Deutschmann and Fals Borda 1962) in which entities switched fully to an innovation without first trying it alongside the incumbent, which reflects abrupt replacement.

As with the extension pattern, much of the research on the replacement patterns (gradual or abrupt) in a channel use context comes from the economics, marketing, and information systems literatures. Just as some studies conclude that new channels are complementary or supplemental to incumbent channels, other studies conclude that the two are substitutes. For example, evidence of substitution has been found for electronic and physical purchasing channels (Langer et al. 2012) and online and print newspaper channels (Gentzkow 2007; Simon and Kadiyali 2007).

Discontinuance (Extension) and Discontinuance (Replacement): The *discontinuance (extension)* and *discontinuance (replacement)* patterns reflect entities that begin to use the new channel but later stop. The difference between the two is whether the entity used the new channel in conjunction with the incumbent channel or exclusively. *Discontinuance (extension)* reflects the former (i.e., entities that transition from using only the incumbent channel to using both channels to using only the incumbent channel; see the Inc→Both→Inc pattern in Table 1). *Discontinuance (replacement)* reflects the latter (i.e., entities that transition from using only the incumbent channel to using only the new channel to using only the incumbent channel; see the Inc→New→Inc pattern in Table 1). We use the term *discontinuance* to be consistent with Rogers, although others use the term *abandonment* (e.g., Burns and Wholey 1993).

Discontinuance of an innovation is a well-documented phenomenon. For example, "disenchantment discontinuance" occurs when an adopter discontinues because s/he is dissatisfied with the innovation's performance (Rogers 2003). This disenchantment can lead the adopter to revert back to the incumbent. *Discontinuance (extension)* may reflect entities that use the new channel on a trial basis, concurrently with their on-going use of the incumbent channel, and later decide that the new channel does not meet their needs. By contrast, *discontinuance (replacement)* reflects entities that switched fully from the incumbent to the new channel without using them concurrently, only to revert back to the incumbent. This likely occurs when it is difficult to use both channels concurrently, perhaps due to the cost of using both channels or to perceived benefits associated with using a single channel exclusively. For example, a new shopping service (such as a web site or mobile app) might attempt to get shoppers to use it exclusively by offering a loyalty/rewards program. This could lead the shopper to abandon the incumbent channel in favor of the new, only to switch back to the incumbent after determining that the new did not meet his needs. One area of research on discontinuance is whether the factors that influence adoption and discontinuance are symmetrical in the sense that an increase in factor A causes adoption while a decrease in factor A causes discontinuance (Burns and Wholey 1993; Fisher et al. 2018).

Retrenchment: The *retrenchment* pattern reflects entities that shift fully to the new channel but then revert back to using both (see the Inc→New→Both pattern in Table 1). We use the term retrenchment because the entity is scaling back its use of the new channel in favor of increased use of the incumbent channel.

Many of the factors that cause an entity to discontinue, such as disenchantment with the innovation or new channel, may also cause an entity to retrench. For example, households who abandon traditional cable television subscriptions in favor of new streaming services (i.e., who "cut the cord") may retrench by re-subscribing to cable after being unsatisfied with the content available in the streaming services (e.g., Prince and Greenstein 2017). Entities that retrench gain some utility from the new channel (albeit perhaps less than they expected) because they continue to use it to some extent. In the context of new and incumbent channels, we suspect that retrenchment may be more common than discontinuance because adopters are likely to find some use for the new channel, even if they overestimated its benefits at initial adoption.

No adoption: The *no adoption* pattern reflects entities that do not use the new channel during the time period analyzed (see the Inc→Inc→Inc pattern in Table 1). We include it for completeness.

Conceptual Development

We explore how entities transition between incumbent and new channels, with a particular focus on the role of two temporal factors: (1) when an entity adopts the new channel, and (2) how long an entity has used the channels. First, we discuss how our analysis of new and incumbent channel use complements and expands upon the traditional adopter categories, which are based on when an entity adopts an innovation such as a new channel. Second, we explore how the length of time that an entity has used the channels (either incumbent or new)—that is, its channel history—affects its transitions between states of new and incumbent channel use. Later in the paper, we examine both of these items empirically.

Adopter Categorization

Although prior research has documented all of the patterns presented in the typology shown in Table 1, no study has analyzed them in a single context. Doing so is important because it permits analysis of when and why entities follow different patterns, while holding the context constant. For example, we are able to analyze whether early adopters of a new channel are more likely to follow a given channel use pattern compared to later adopters. We are also able to explore whether entities that adopt at similar times follow similar or divergent channel use patterns.

This allows us to expand upon the traditional adopter categories. These categories, which consist of innovators, early adopters, early majority, late majority, and laggards, are so well-established that they are "essentially the only method of adopter categorization" (Rogers 2003, p. 282). They remain in common use (e.g., Kotler and Keller 2016). The typology (Table 1) illustrates that adopters in each of the categories can be further classified based on their post-adoption channel use behaviors. For example, innovators, early adopters, etc., may follow drastically different post-adoption use patterns: some may extend, some may replace, some may discontinue, and some may retrench. Recognizing these "categories within categories" is important for adoption researchers, managers, and policy makers because it has implications for measuring the success of the new channel, predicting its continued diffusion, understanding how/whether to continue investment in the incumbent channel, etc. For example, if most innovators follow an immediate replacement pattern, then it may be possible to phase out the incumbent channel relatively quickly. Conversely, if most innovators follow an extension or a retrenchment pattern, then continued investment in and maintenance of the incumbent channel may be required. Below, we explore empirically whether entities that adopt at similar times follow different new/incumbent channel use patterns.

The traditional adopter categorization system describes the characteristics of adopters in each category. For example, "innovators" are considered to be venturesome, the "early majority" are considered to be opinion leaders, the "late majority" are considered to be skeptical of innovation, and "laggards" are considered to be traditionalists (Kotler and Keller 2016; Rogers 2003, pp. 282-284). This assumes (implicitly) that there is a fixed population of potential adopters at a given time t, each of whom adopts the innovation at a different time. This is a reasonable assumption in many situations and is valuable for understanding innovation diffusion. However, in other situations it is useful to recognize that a new cohort joins the population of potential adopters in each time period, rather than to fix the population as it stands at a given time. For example, consider the adoption of online distance education for college courses, which is a new channel compared to the incumbent channel of taking college courses on a physical campus. Each year, a new cohort joins the population of potential adopters of online distance education for college courses: students graduating from high school. In such a situation, characterizing adopters solely based on when they adopt is incomplete. For example, it could be that those who adopt relatively late are quite innovative and are not laggards, with their late adoption simply reflecting their late entry into the population of potential adopters. We explore this further by examining the role of entities' *channel history*.

Entities' Channel History

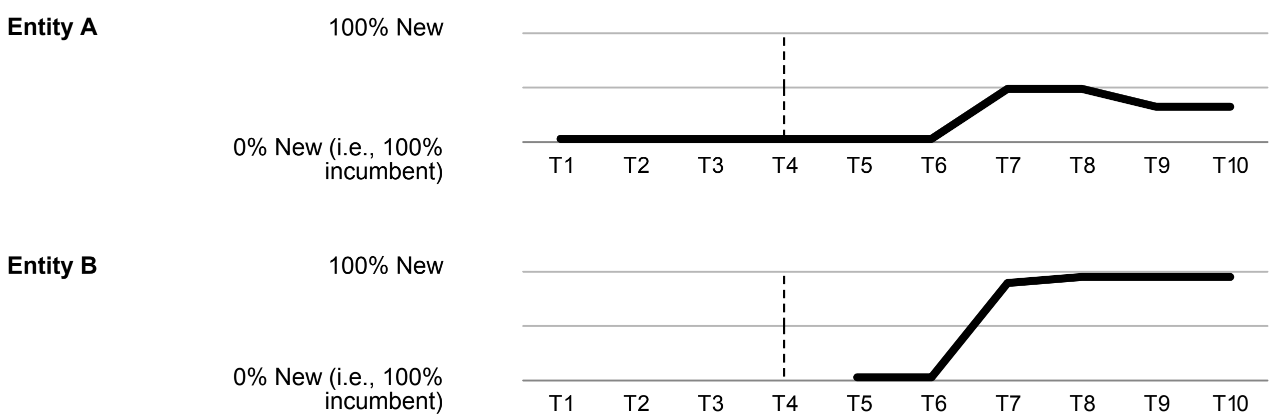
Many factors affect how entities transition between states of new/incumbent channel use over time, which creates entities' channel use patterns. We focus our theorizing on how long an entity has been using either channel, which we refer to as *channel history*. To illustrate this idea, consider two entities. One (A) used the incumbent channel before the new channel was introduced, while the other (B) began using the channels after the new channel was introduced. At each point in time, Entity A has a longer channel history than does Entity B.

We consider how channel history affects entities' use of the new *vis-à-vis* the incumbent channel. On one hand, the longer an entity's channel history, the more likely it has used the incumbent channel for a long time. As a result, entities with long channel histories may have established habits or routines of using the incumbent channel that impede their ability or interest to transition to the new channel (e.g., Neslin and Shankar 2009). A related phenomenon exists in the context of information system acceptance: preexisting habits, such as those associated with using an incumbent system, hinder acceptance of new technologies (Polites and Karahanna 2013). On the other hand, entities with long channel histories are likely to have a deep understanding of the pros and cons of the incumbent channel and the potential benefits offered by the new channel (e.g., Ansari et al. 2008; Valentini et al. 2011). A desire to capture these benefits could cause these entities to transition to the new channel quickly. Rogers' innovation-decision model (2003, see Chapter 5) provides support for this perspective by describing how knowledge and understanding are precursors to adopting an innovation.

These two perspectives, which we label *channel habit* and *channel understanding*, are seemingly in conflict. To resolve this, we used *temporal separation* (Poole and Van de Ven 1989), which seeks to resolve a conflict between different perspectives by recognizing that both perspectives may apply, but at different times. We posit that channel understanding will cause entities with long channel histories to adopt the new channel initially (to capture the benefits they anticipate), while channel habit will cause those entities to continue using the incumbent channel over time (given the force of habit). Thus, both perspectives apply, with the channel understanding perspective applying primarily when the new channel is first adopted and the channel habit perspective applying throughout. This suggests that even though entities with long channel histories may be early adopters of the new channel, they are likely to follow an extension or retrenchment pattern, given their habit of using the incumbent channel. Entities with short channel histories may also be early adopters, but they are likely to follow a replacement pattern, because they have relatively little habit using the incumbent channel. In other words, channel history will affect an entity's channel use after adopting the new channel, but it will not necessarily affect when the entity adopts. We depict this argument graphically in Figure 1, and we explore it in our empirical context.

Empirical Context and Data

We use the wholesale used vehicle market as the context for our empirical analysis. This market is a business-to-business market in which buyers and sellers exchange used vehicles. Buyers in the market are used car dealers who purchase vehicles to resell to retail customers. Sellers in the market include used car dealers (who sell vehicles they do not retail), automotive manufacturers or their finance arms (e.g., Toyota, Toyota Financial Services), rental car companies, and banks. An intermediary (referred to as an automotive auction company in the industry) brokers transactions between buyers and sellers. The market has traditionally operated as a physical market: buyers, sellers, and vehicles are collocated at physical facilities operated by an intermediary. The intermediary groups vehicles by type and/or seller and auctions them sequentially—one at a time—in a *sales event*. Some sales events are open to all dealers, while others are restricted to only those dealers who have a relationship with the seller. Typically, sellers in restricted sales events are automotive manufacturers (or their finance arms), while buyers are their franchised dealers (e.g., Toyota selling to Toyota franchised dealers). Multiple sales events occur at a facility on a given day. Used car dealers attend the physical facilities to purchase vehicles auctioned in these sales events. In the early 2000's, the intermediary made electronic channels available to dealers. The most popular is the webcast channel, which provides a live audio/video feed via the internet of the sales events occurring at the physical facilities. Dealers access this feed via a browser-based application that allows them to place bids in competition with the dealers physically present at the facility. This allows them to purchase vehicles that are auctioned at the physical facility without making a trip to the facility. The intermediary deployed the webcast channel in stages across their physical locations over time. Thus, not all sales events were available via the webcast channel during our study period, although an increasing number became available over the period. (We exploit this for measurement



Notes: The figure denotes the percentage of new channel use relative to total channel use (i.e., new + incumbent use; y-axis) over time (x-axis) for two entities: A and B. Entity A has a longer channel history than does Entity B, which does not use either channel until the fifth time period: T5. The dotted vertical line indicates that the new channel became available at T4. Both entities adopt the new channel at the same time (at T6). However, Entity A follows a retrenchment pattern, while Entity B follows a replacement pattern, theoretically because of Entity A's longer channel history (as discussed in the text).

Figure 1. Illustration of the Posited Effect of Channel History on Channel Use

purposes, as discussed below.) Importantly, the webcast channel is not a stand-alone electronic market; rather, it is an internet access channel for the auctions occurring in the physical channel. This means that (1) any vehicle that is available to buyers using the webcast channel is also simultaneously available to buyers using the physical channel (although not necessarily vice-versa), and (2) there is a single price for each vehicle that is determined by the bidding competition between buyers using the physical and webcast channels (as opposed to a physical channel price and an electronic channel price).[4]

Data

An intermediary that operates physical facilities as well as the webcast channel provided data on 52,007,685 vehicles auctioned in the wholesale used vehicle market (of which 30,625,189 were purchased) from January 1, 2003, to March 31, 2009. The data allow us to observe how dealers use the electronic (webcast) and physical channels to make purchases over time; in other words, we observe how dealers use both the new channel and the incumbent channel over time. We use a 6.25 year time span so that there is sufficient time for channel use patterns to emerge. For each purchase transaction, the data contain an identifier for the purchasing dealer (*DealerID*), the dealer's zip code (*DealerZip*), the vehicle's odometer reading (*Mileage*), the vehicle's year, make, and model (*YearMakeModel*, e.g., 2007 Toyota Camry), the transaction price (*Price*), the transaction date (*SaleDate*), the sales event in which the transaction occurred (*SalesEvent*), whether the sales event was restricted to only those dealers who have a relationship with the seller (*Restricted*, coded as an indicator variable), and whether the dealer who purchased the vehicle used the electronic channel or the physical channel (*Electronic*, coded as an indicator variable.) We also gathered the zip code of each of the physical facilities (*FacilityZip*).

We structured the data as a panel in which *DealerID* was the panel variable and quarter the time variable. This panel structure facilitated our analysis of how dealers' electronic purchasing *vis-à-vis* physical purchasing evolved over time. For each dealer i in quarter t, we computed $PPurchases_{it}$ and $EPurchases_{it}$ as the number of vehicles purchased physically and the number of vehicles purchased electronically, respectively. We also computed $Purchases_{it} = PPurchases_{it} + EPurchases_{it}$ and $PctElecPurchases_{it} = EPurchases_{it} / Purchases_{it}$.

[4]Another electronic channel is a standalone electronic system in which vehicles are listed on web pages. This system functions similarly to eBay: buyers purchase vehicles at a "Buy Now" price or by bidding in an ascending auction. Use of this channel was rare during our study period; only 0.7% of the vehicles purchased in our data were via this channel. Given this, we focus on use of the webcast channel. Including transactions that occurred in the standalone electronic channel has no substantive impact on our analysis.

Analysis and Results

Adopter Categorization

We begin by analyzing the incumbent and new channel use patterns that dealers followed over time. This allows us to validate the typology and to examine whether entities that adopt the new channel at similar times follow different channel use patterns.

Empirical Validation of the Typology

To empirically validate the typology, we examined how dealers' channel use patterns evolved over the 6.25 years of our sample period. We focused this aspect of our analysis on the dealers who made purchases in each of the 25 quarters contained in our data. There were 13,030 such dealers; they purchased 12,949,273 vehicles (or 42.3% of the vehicles purchased). Focusing on these dealers allowed us to study a set of entities who were active channel users over the same time period, which facilitates our analysis of whether those that adopted the new channel at similar times followed different channel use patterns. Furthermore, this allowed us to examine how dealers' use of the new vis-à-vis the incumbent channel evolved from the time the new channel was essentially first introduced. Indeed, 99.2% of these dealers made only physical purchases in Q1-2003. Results are consistent if we drop the 0.8% of dealers who made electronic purchases and if we include dealers who did not purchase in each quarter, which includes those whose first observed purchase occurred later in the sample time period (see the appendix).[5]

First, we plotted the $PctElecPurchases_{it}$ values by quarter for several dealers. Figure 2 shows these plots for four dealers and illustrates four different use patterns: discontinuance (replacement) (first panel; this dealer began purchasing exclusively via the electronic channel in 2006 but stopped by 2008), extension (second panel; this dealer purchased via both channels from approximately 2005 on), abrupt replacement (third panel; this dealer shifted immediately from 0% to 100% electronic purchasing in 2004), and retrenchment (fourth panel; this dealer reached 100% electronic purchasing but then reverted to 20%–50% electronic purchasing).

There are 13,030 such plots in the data, one for each dealer included in this analysis. We used k-means clustering to categorize the use patterns of the 13,030 dealers based on their $PctElecPurchases_{it}$ values in each quarter. Prior to the cluster analysis, we removed all dealers who never used the electronic channel; there were 3,696 such dealers. We assigned these dealers to the "No Adoption" pattern. For the remaining 9,334 dealers, we calculated k-means solutions using 6, 8, 10, 12, and 14 clusters. We determined the 12-cluster solution to be optimal, as fewer clusters were too high-level to reveal the heterogeneity of use patterns and more clusters fragmented the 12-cluster solution without yielding additional insight.[6] For each cluster, we plotted the mean and median values of $PctElecPurchases_{it}$ for each quarter to inspect the average use patterns followed by dealers in the cluster. Plots of the median values appear in Figure 3. Figure 3 also shows the median number of purchases per quarter by the dealers in the cluster; this illustrates that changes in the median $PctElecPurchases_{it}$ values are not skewed by variation in $Purchases_{it}$, which is the denominator of $PctElecPurchases_{it}$. Of the 9,334 dealers included in the cluster analysis, 5,226 dealers purchased via the electronic channel so minimally that the median values of $PctElecPurchases_{it}$ for these dealers in each quarter were 0. We placed these dealers in the "No Adoption" cluster, along with the 3,696 dealers who never used the electronic channel.

The patterns proposed in the typology are evident in the data, and no major patterns in the data are missing from the typology. We use the column headings in Figure 3 to note that the patterns reflect those in the typology, placing arrows between the Extension, Retrenchment, and Discontinuance (Extension) headings to note the subjectivity associated with assigning labels to the patterns (in particular, exactly how much of a decline in the percentage of electronic purchasing is necessary for retrenchment is subjective).[7] Two of the patterns suggested by the typology—abrupt replacement and discontinuance (replacement)—are not evident in the cluster analysis shown in Figure 3. This does not mean that these patterns are not evident in the data (indeed, Figure 2 provides an example of each), only that they are not prevalent enough for the k-means routine to define a distinct cluster for them.

[5] Of the dealers who did not purchase in each quarter, 95.9% made only physical purchases in their initial period. Thus, an assumption we used to derive the typology of use patterns—that all entities are in the incumbent state in their initial period—accurately reflects the overwhelming majority of dealers in our analysis. It also means that the overwhelming majority of dealers' initial experience with the channels (which affects their channel history) was with the physical channel.

[6] Following Bapna et al. (2004), we calculated the dissimilarity ratio for each solution, which is the mean distance between clusters (the *intercluster* distance) divided by the mean distance of each observation to its cluster center (the *intra-cluster* distance). Higher ratios indicate more distinct clustering. We chose the 12-cluster solution because it had the highest dissimilarity ratio.

[7] Subjectivity in how empirical entities are assigned to categories within a typology is common in the social sciences. For example, the precise breakpoints between prospectors, analyzers, and defenders in Miles and Snow's (1978) well-known typology of firm strategies are subjective.

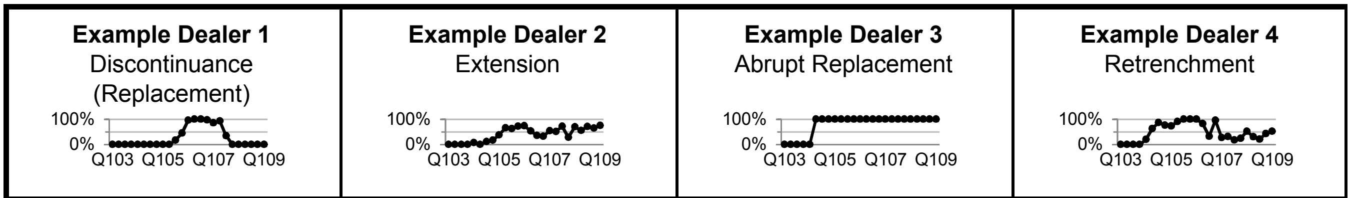
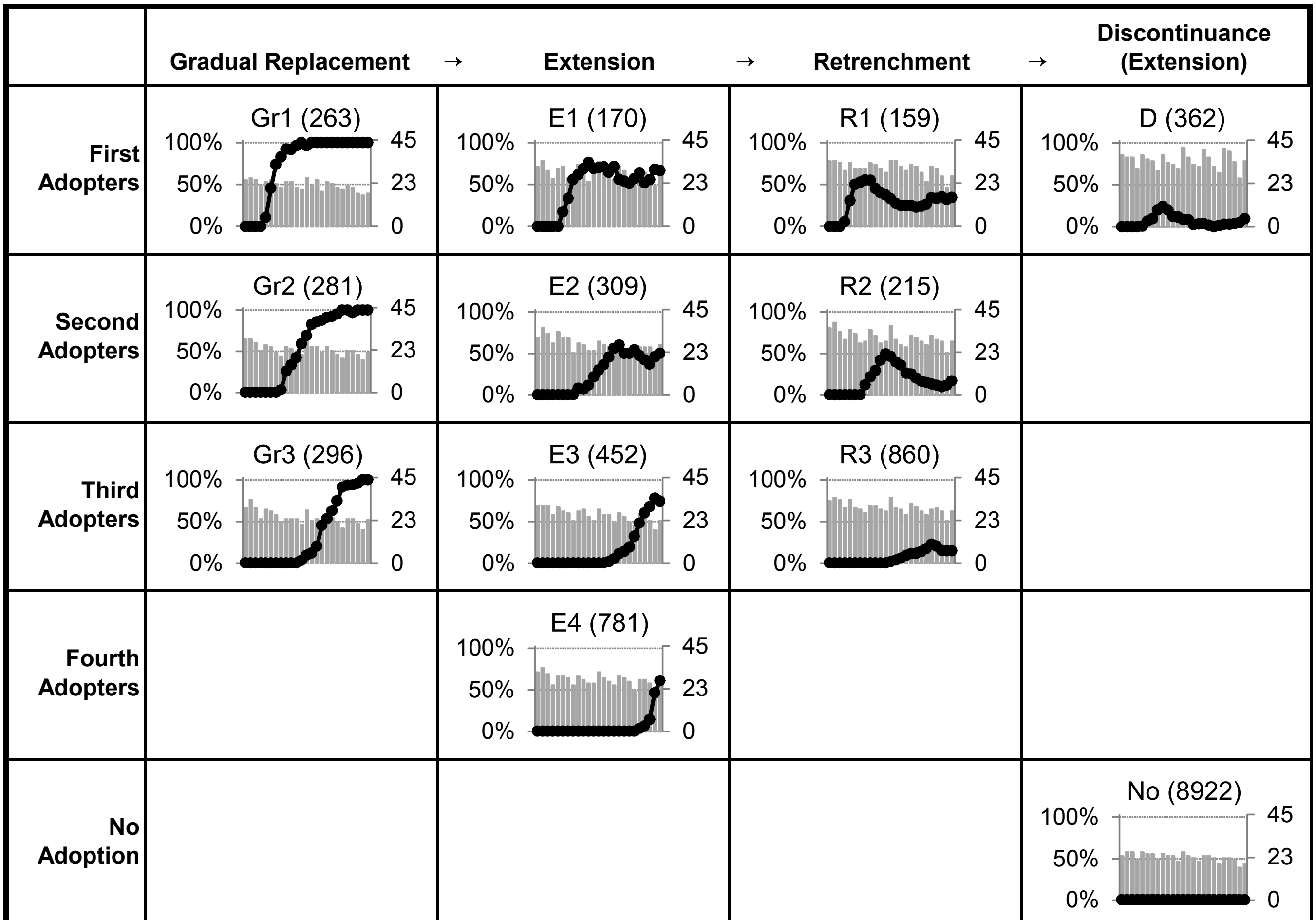


Figure 2. Percentage of Electronic Purchasing (y-axis) over Time (x-axis) for Four Illustrative Dealers



Notes: Plots depict the median value of $PctElecPurchases_{it}$ (left-hand y-axis, black dots) and the medium value of $Purchases_{it}$ (right-hand y-axis, gray bars) per quarter (x-axis) for the dealers in a cluster. Cluster analysis based on $PctElecPurchases_{it}$ values only. Each cluster is labeled in accordance with the typology, with the number of dealers per cluster in parentheses. Gr = Gradual Replacement; E = Extension; R = Retrenchment; D = Discontinuance; No = No Adoption. The rows depict clusters in which the dealers adopted the new channel relatively early ("First Adopters" row), a few quarters later ("Second Adopters" row), and so on. The columns depict the pattern followed by the dealers in each cluster.

Figure 3. New and Incumbent Channel Use Patterns from the k-Means Cluster Analysis

The Figure 3 results illustrate that most dealers who ultimately replace the incumbent physical channel with the new electronic channel transition through a period in which they purchase via both channels. In other words, there appears to be a learning or assimilation period involved.

Do Dealers Who Adopt at Similar Times Follow Different Channel Use Patterns?

Figure 3 shows that dealers who adopted the electronic channel at similar times followed different channel use patterns. The first row shows the clusters that represent the average use patterns of dealers who were the first to adopt the electronic channel. According to the traditional typology, these dealers would be categorized as innovators or early adopters.[8] Figure 3 shows that after adoption, the use patterns of these dealers diverge, often quite dramatically. For example, some dealers (approximately 28%) continued to increase their percentage of electronic purchasing until they completely abandoned the incumbent physical channel. In other words, they followed a gradual replacement pattern. Other dealers (approximately 34%) continued to use both channels (see the second and third columns). Those in the second column followed an approximate extension pattern, and those in the third column followed more of a retrenchment pattern. The other dealers (the remaining 38%) essentially abandoned the electronic channel after having previously adopted it (see the fourth column). These dealers followed an approximate discontinuance (extension) pattern, although with a minor amount of electronic purchasing (on average) at the end of the time period. This heterogeneity is evident for later adopters as well as the initial adopters (see rows 2 and 3 of Figure 3).

Entities' Channel History

A central theme of our analysis is that entities transition between different states of new and incumbent channel use (or remain in the same state) over time, which forms their channel use patterns. As motivated in our conceptual development, we analyze how variation in entities' channel history, along with several other variables, influences these transitions.

Model-Free, Descriptive Analysis

Prior to presenting our formal model, we present model-free analysis of the influence of channel history. This analysis is based on a set of transition matrices that summarize how dealers transition between states of new and incumbent channel use over time. In the typology presented above, we used three states: Incumbent, Both, and New. For the empirical analysis that follows, we divided the Both state into a "mostly incumbent" and a "mostly new" state, labeled Both (Mostly Inc) and Both (Mostly New). We placed dealer i at time t in the Incumbent state if $PctElecPurchases_{it} = 0$, in the Both (Mostly Inc) state if $PctElecPurchases_{it} > 0$ and $PctElecPurchases_{it} \leq 0.5$, etc. We used two Both states because this better leverages the variation in the data. (We achieve similar results if we use three Both states with breakpoints at 0.33 and 0.67.) At each time t, dealers can transition to a new state or remain in their current state. The transition matrix presents the counts of transitions between states (including transitions in which a dealer stays in the same state), along with transition probabilities.[9]

We created a matrix for all dealers in the data as well as separate matrices for dealers whose first observed purchase occurred in 2003, 2004, 2005, 2006, 2007, and 2008 (which we call "cohorts"). The matrices by cohort provide an initial view of the role that channel history plays in how dealers transition between channels. This is because dealers in the 2008 cohort have a shorter channel history than do dealers in the 2003 cohort.

We first present the transition matrix for all dealers, shown in Table 2. A few points are worth highlighting. First, states are relatively "sticky" in the sense that dealers in a given state are more likely to remain there than to transition to any other state. When dealers do transition, they are most likely to transition to a state that closely resembles their current state, as opposed to "jumping" states. Second, there are several instances in which dealers transition from states involving more electronic purchasing to states involving less electronic purchasing. For example, dealers in the Both (Mostly Inc) state transition to the Incumbent state 36% of the time. However, once a dealer transitions to the Both (Mostly New) state, it becomes less likely that he will transition back to the Incumbent state, either directly or via a transition to the Both (Mostly Inc) state. This suggests a tipping point at which high levels of new channel use are more likely to be sustained over time.

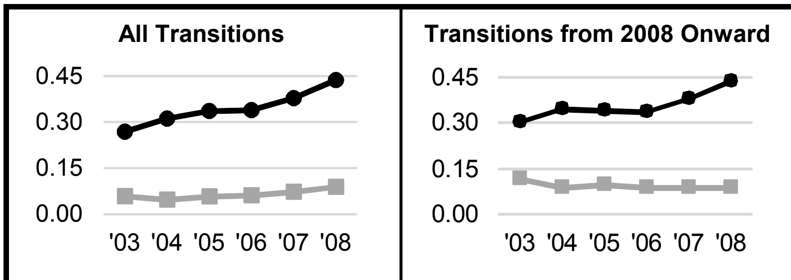
[8]Rogers (2003, p. 280) defined the first 2.5% of entities in a system to adopt to be innovators. He defined the next 13.5% to be early adopters. There were 63,823 dealers who made purchases in Q1-2003. The first 2.5% of these entities had adopted the electronic channel by Q3-2003, and the next 13.5% had adopted by Q1-2005. Thus, entities in the first row of Figure 3—who adopted the electronic channel in Q1-2004 (on average)—would be categorized as innovators or early adopters.

[9]For dealers with gaps in their quarterly purchasing behavior, we set their state in the t-1 quarter as their state in the most recent quarter in which they purchased.

Table 2. Counts and Probabilities (in Parentheses) of State Transitions for All Dealers

		State at Time *t*				
		Incumbent	**Both (Mostly Inc)**	**Both (Mostly New)**	**New**	**Total**
State at time *t*-1	**Incumbent**	956,463 (0.93)	59,206 (0.06)	6,044 (0.01)	9,778 (0.01)	1,031,491 (1.0)
	Both (Mostly Inc)	45,702 (0.36)	64,032 (0.51)	11,412 (0.09)	5,470 (0.04)	126,616 (1.0)
	Both (Mostly New)	3,432 (0.09)	9,001 (0.25)	15,429 (0.43)	8,437 (0.23)	36,299 (1.0)
	New	5,911 (0.14)	4,176 (0.10)	6,941 (0.17)	23,969 (0.58)	40,997 (1.0)
	Total	1,011,508	136,415	39,826	47,654	1,235,403

Note: Probabilities across each row sum to 1 (with rounding error).



- Upper series: Probability of state transition from Both (Mostly Inc) or Both (Mostly New) to New
- Lower series: Probability of state transition from Inc to Both (Mostly Inc) or Both (Mostly New)

Note: The x-axis represents the cohort of dealers whose first observed purchase occurred in each year.

Figure 4. State Transition Probabilities (y-axis) for Dealers Whose First Observed Purchase Occurred in Each Year (x-axis)

Figure 4 summarizes findings from the transition matrices for each cohort. We focus on two types of transitions, those from the Incumbent state to one of the Both states and those from one of the Both states to the New state. This allows us to assess the effect of channel history on (likely initial) transitions from using the incumbent channel to using both channels as well as its effect on (likely later) transitions to using only the new channel. The first column of Figure 4 shows that dealers in all cohorts were similarly likely to transition from the Incumbent state to one of the Both states. However, dealers in the later cohorts (i.e., who had shorter channel histories) were substantially more likely to transition from one of the Both states to the New state (i.e., to follow a replacement pattern). Of course, the electronic channel was more mature in terms of its functionality and reliability in the later years of the sample than in the earlier years. This could explain why dealers in the later cohorts were more likely to transition to the New state. Given this, the second column of Figure 4 shows the same results using only transitions from 2008 onward. This yields a similar picture. From 2008 onward, dealers in the early cohorts had a similar likelihood as dealers in the later cohorts to transition from the Incumbent state to one of the Both states, but a lower likelihood to transition from one of the Both states to the New state. In other words, dealers in the early cohorts (who have longer channel histories) are more likely to follow an extension or retrenchment pattern, while dealers in the later cohorts are more likely to follow a replacement pattern. This is consistent with our conceptual development regarding the role of channel history. We explore this relationship more formally in the next section.

Econometric Model

We used a discrete choice model to analyze the factors, including channel history, that influence how dealers transition between states of channel use. The intuition behind the model is that dealer i chooses at time t whether to remain in the state of channel use that he was in at time t-1 or to transition to a new state. We defined four states (Incumbent, Both (Mostly Inc), Both (Mostly New), and New) to mirror the model-free analysis, and we placed each dealer into one of these four states in each quarter t based on his $PctElecPurchases_{it}$. (Analysis based on a single Both state and on three Both states [with breakpoints at 0.33 and 0.67] yields similar results.)

Dealer i chooses the state that provides him with the highest utility (e.g., Train 2009). The utility of each state s for dealer i at time t is $U_{ist} = \alpha_{is} + \beta_s' X_{it} + \sum_{t=2}^{24} \gamma_{st} time_t + \varepsilon_{ist}$; we describe each term below. The probability that dealer i chooses state s at time t from among all possible states S is

$$p_{ist} = \frac{\exp\left(\alpha_{is} + \beta_s' X_{it} + \sum_{i=2}^{24} \gamma_{st} time_t\right)}{\sum_{s=1}^{S} \exp\left(\alpha_{is} + \beta_s' X_{it} + \sum_{i=2}^{24} \gamma_{st} time_t\right)}$$

We use a mixed logit model, which is an extension to the multinomial logit model (for details, see Train 2009).

α_{is} is a normally distributed random intercept that captures the latent utility of each state s for each dealer i. X_{it} contains variables that influence each dealer's choices at each time t, which we discuss below. β_s' are associated coefficients. $time_t$ are indicator variables for each of the 24 time periods in which we observe transitions. They control for the maturity and functionality of the electronic channel (as well as other time-varying factors like seasonality), which as noted above increased over time. γ_{st} are associated coefficients. ε_{ist} is an error term with a type 1 extreme value distribution (as is standard in discrete choice models).

Explanatory Variables: One of the variables in X_{it} is $ChannelHistory_{it}$. To create $ChannelHistory_{it}$, we recorded the quarter in which we first observed each dealer i to make a purchase, which we labeled $FirstPurchaseQuarter_i$. We then defined $ChannelHistory_{it}$ as the number of quarters between $FirstPurchaseQuarter_i$ and time t. For example, if dealer i's first purchase occurred in Q4-2005, then his $ChannelHistory_{it}$ would be 1 in Q1-2006, 2 in Q2-2006, etc. Including the $time_t$ variables in the model allows us to separate the $ChannelHistory_{it}$ effect at time t from the maturity / functionality of the electronic channel at time t.

To help isolate the effect of channel history, we included in X_{it} other variables likely to influence dealers' state transitions. We used theory and prior literature to help us identify these variables. As described by Nan et al. (2014), including in a single study the full range of variables known to influence adoption and use of an innovation such as a new channel is impractical and generally not done. Nan et al. adapted the awareness–motivation–capability (AMC) framework (Chen and Miller 2012) to capture the spirit of most of these variables in a parsimonious way. They proposed that to adopt an innovation, an entity must have sufficient *awareness* of the innovation, sufficient *motivation* to want to adopt it, and sufficient *capability* to adopt it successfully. We used this framework to identify variables likely to influence dealers' awareness, motivation, and capability to use the new electronic channel, including how this might relate to their use of the incumbent physical channel. Although the variables that we identify are unlikely to be exhaustive, they represent each dimension of the AMC framework.

Innovation diffusion theory posits that an entity's geographic neighbors can increase a potential adopter's *awareness* of and *motivation* to use an innovation such as a new channel (Howells and Bessant 2012; Mohammed 2001; Rogers 2003). This is because communication between neighbors raises awareness of an innovation (Ansari et al. 2008). Neighbors may also create normative/mimetic pressures that motivate an entity to use an innovation (e.g., Angst et al. 2010). Thus, we included $PctElec\_GeoNeighbors_{it}$ in X_{it}, which is the percentage of electronic purchasing by dealers within 50 miles of dealer i in quarter t (based on dealer zip codes), not including dealer i.[10]

Another variable likely to influence a dealer's *motivation* to use the new channel is the transaction cost of using the incumbent channel. Economic theory posits that entities choose channels with low transaction costs, *ceteris paribus* (e.g., Balasubramanian 1998; Hotelling 1929; Jeffers and Nault 2011). One of the key factors that influences transaction costs is geographic location. If an incumbent, physical channel requires an entity to travel a long distance, then the transaction costs for that channel may be high, thereby motivating the entity to use a new, electronic channel that doesn't require travel. To account for this, we included $DistanceClosestFacility_{it}$ in X_{it}, which is the distance in miles from dealer i's location to the nearest physical facility (as measured by the dealer's and facility's zip codes).

The number of vehicles that a dealer purchases may also influence his *motivation* to use the electronic channel. One finding from prior research is that using both new and incumbent channels provides an entity with expanded opportunities to fulfill its consumption needs. For example, patients who need frequent and recurring medical care often adopt telemedicine (Wootton 2012), often in addition to their use of existing physical care facilities (Palen et al. 2012). Also, many high-volume consumers continue to buy at physical stores after adopting electronic commerce (Neslin and Shankar 2009). This suggests that dealers with high purchase volumes are likely to transition to states in which they use both channels. To account for this, we included $Purchases_{it}$ in X_{it}.

[10]We also used a threshold of 100 miles and achieved similar results.

The fit of each channel to a dealer's needs is likely to influence his *motivation* and *capability* to use the channels. Economic theory suggests that if a channel's fit is low, perhaps due to the selection or quality of products/services in the channel, then an entity will be less motivated to use the channel and/or will not be able to use it effectively (Forman et al. 2009; Viswanathan 2005). We included two fit measures in X_{it}: $FitElec\_VehicleType_{it}$ and $(Mis)FitElec\_Mileage_{it}$. $FitElec\_VehicleType_{it}$ captures the extent to which the vehicles that dealer *i* purchased at time *t* were available in the electronic channel, which we measured as follows. First, we calculated $PctSupplyElec_{jt}$ by dividing the number of vehicles of year/make/model *j* (e.g., 2007 Honda Accord) that were available in sales events that were webcast in quarter *t* (recall that not all sales events are webcast) by the number of vehicles of year/make/model *j* that were available in all sales events in quarter *t*.[11] In general, $PctSupplyElec_{jt}$ increased over time as the webcast channel was more widely deployed at the physical facilities. Second, for dealer *i* in quarter *t*, we counted the number of vehicles of each year/make/model *j* he purchased ($Purchases_{ijt}$). Third, we took the weighted average of $PctSupplyElec_{jt}$ for each of the year/make/models *j* that dealer *i* purchased in quarter *t*, with the weights determined by $Purchases_{ijt}$. For example, assume that dealer *i* in Q104 purchased one 2002 BMW 3-Series (with $PctSupplyElec_{jt}$ = 0.48) and three 2002 Toyota Corollas (with $PctSupplyElec_{jt}$ = 0.28). His $FitElec\_VehicleType_{it}$ measure in Q104 would be 0.33 (i.e., ¼*0.48 + ¾*0.28). $FitElec\_VehicleType_{it}$ also accounts for the positive role that network effects play in dealers' use of the electronic channel. This is because as more vehicles are made available in the electronic channel (which is reflected in an increase in $FitElec\_VehicleType_{it}$), the more valuable the electronic channel becomes to dealers. $(Mis)FitElec\_Mileage_{it}$ captures the extent to which the dealer purchases the type of vehicles that are best suited for electronic trading. Used vehicles of high quality uncertainty trade better physically than electronically (e.g., Overby and Jap 2009). The quality uncertainty of a used vehicle increases with its mileage, because high mileage vehicles are more likely to have developed quality-related issues than low mileage vehicles (Genesove 1993). Thus, dealers who purchase low mileage vehicles are likely to have better fit to the electronic channel than are dealers who purchase higher mileage vehicles. Therefore, we measure $(Mis)FitElec\_Mileage_{it}$ as the average mileage of the vehicles purchased by dealer *i* at time *t*. $(Mis)FitElec\_Mileage_{it}$ is a reverse-coded measure (hence the "*(Mis)*" prefix), because as this measure increases, the fit between the dealer and the electronic channel should decrease.

Exposure to similar innovations is likely to influence a dealer's *capability* to use the new channel effectively. Innovation diffusion theory suggests that a key component of the adoption process is gaining an understanding of how an innovation works and what it does (Rogers 2003). Entities with exposure to similar innovations are likely to have this understanding already or be able to develop it quickly, thereby speeding their adoption and increasing their capability to use the innovation effectively. To account for this, we included $PctRestricted_{it}$ in X_{it}, which is the percentage of vehicles that dealer *i* purchased in restricted sales events in quarter *t* (see the "Data" subsection above for a description of the *Restricted* variable on which this measure is based). Dealers who participate in restricted sales events are typically franchised dealers who are purchasing from their franchisor manufacturers (e.g., Ford, Toyota). During the time period of our study, most manufacturers provided electronic systems for their franchised dealers to order new vehicles; these systems are similar to the electronic channel for purchasing used vehicles that we study. Thus, we reasoned that dealers with high values of $PctRestricted_{it}$ had more exposure to innovations similar to the electronic channel.

Table 3 shows descriptive statistics, including those for the variables included in X_{it}.

Model Estimation and Results

The influence of the explanatory variables may differ based on what state the dealer is in (e.g., Valentini et al. 2011). For example, dealers who purchase a high volume of vehicles may choose to use both channels, because that gives them expanded opportunities to fulfill their demand. In this case, $Purchases_{it}$ will be positively correlated with a transition from the Incumbent state (which involves only one channel) to one of the Both states but negatively correlated with a transition from one of the Both states to the New state (which also involves only one channel). To accommodate this state dependence, we estimated the model in four stages, with stage 1 containing the observations for dealers who were in the Incumbent state at time *t*-1, stage 2 containing the observations for dealers who were in the Both (Mostly Inc) state at

[11]We categorized a sales event as being webcast if at least one vehicle in the sales event was purchased by a dealer using the webcast channel.

Table 3. Descriptive Statistics for Variables

	Mean (S.D.)	Correlations 1	2	3	4	5	6	7	8
1: $PctElecPurchases_{it}$	0.08 (0.24)	1.00							
2: $ChannelHistory_{it}^{a}$	1.01 (0.66)	0.16	1.00						
3: $DistanceClosestFacility_{it}^{b}$	0.51 (0.63)	0.14	0.02	1.00					
4: $FitElec\_VehicleType_{it}$	0.48 (0.26)	0.33	0.57	0.11	1.00				
5: $(Mis)FitElec\_Mileage_{it}^{c}$	0.68 (0.45)	-0.23	-0.07	-0.15	-0.46	1.00			
6: $PctElec\_GeoNeighbors_{it}$	0.09 (0.08)	0.24	0.43	0.38	0.48	-0.06	1.00		
7: $PctRestricted_{it}$	0.12 (0.28)	0.26	0.03	0.18	0.31	-0.43	0.08	1.00	
8: $Purchases_{it}^{b}$	0.22 (0.45)	0.00	0.02	-0.03	0.04	-0.09	-0.04	0.07	1.00

n = 1,235,403. All correlations are significant at $p < 0.01$. [a,b,c] variables scaled by dividing by 10 (a), 100 (b), and 100,000 (c).

Table 4. Fit Statistics for Each Stage of the Mixed Logit Model

State at *t*-1	n	Log likelihood	Pseudo-R^2
Incumbent	1,031,491	-318663	0.12
Both (Mostly Inc)	126,616	-135408	0.08
Both (Mostly New)	36,299	-46344	0.08
New	40,997	-46144	0.08

Note: Pseudo-R^2 is 1 − (log likelihood of full model/log likelihood constant-only model).

time *t*-1, etc.[12] We included observations for all dealers who purchased in at least two quarters in this analysis (two quarters are necessary for us to observe a transition). For dealers with gaps in their quarterly purchasing behavior, we set their state in the *t*-1 quarter as their state in the most recent quarter in which they purchased. Results are similar if we restrict the analysis to only those dealers who purchased in all 25 quarters of the study period (reported in Table A2 of the appendix), although we cannot estimate the influence of $ChannelHistory_{it}$ in that analysis because it does not vary across dealers in that subsample. We also estimated an omnibus model in which we included all of a dealer's observations (regardless of his state at time *t*-1). By including all of a dealer's observations in a single model, we can better account for dealers' unobserved channel preferences, which we model via the normally distributed random intercepts (α_{is}). Results are similar to our focal results; see the appendix for details. Fit statistics for each stage of model estimation appear in Table 4.

Coefficient estimates appear in Table 5. Multinomial (and mixed) logit models produce coefficients for each alternative (in our case, each state) that represent how much a change in a variable influences the probability of choosing that alternative, relative to a base alternative. Thus, Table 5 shows 12 rows of coefficients, one for each combination of the 4 states

[12]The need to accommodate state dependence is one reason that we used a choice model approach. We list each reason here. First, because dealers in our analysis make choices about their channel use, the choice model approach is natural for our purposes. Second, our conceptual analysis is based on entities choosing among different states of new and incumbent channel use over time, and the choice model approach models this directly. Third, the choice model approach is well-suited for analyzing which factors influence these choices, which is our goal for this aspect of our analysis. Fourth, the choice model approach allows us to accommodate state dependence in a straightforward manner. For example, we can examine whether the effect of a variable differs based on whether the dealer is transitioning from the Incumbent state or from one of the Both states. It also allows the effects of variables to be asymmetric (i.e., to have a different effect on the probability of transitioning to states involving a higher percentage of new channel use than on the probability of transitioning to states involving a lower percentage of new channel use). Fifth, the choice model approach allows us to analyze whether the effects of the explanatory variables are nonlinear. For example, an explanatory variable might have a major impact on the probability of an entity moving from 0% to 10% new channel use (i.e., of transitioning from Incumbent to Both (Mostly Inc)) but little impact on moving from 90% to 100% new channel use (i.e., of transitioning from Both (Mostly New) to New). Sixth, the choice model approach allows us to analyze the probability of entities making dramatic shifts in channel use, such as jumping directly from 0% incumbent channel use (i.e., the Incumbent state) to 100% new channel use (i.e., the New state.)

Table 5. Results of Mixed Logit Model to Examine Dealer Transitions Between States of Incumbent and New Channel Use

State Transitions								
From	**To**	***Channel History$_{it}^{a}$***	***DistanceClosestFacility$_{it}^{b}$***	***FitElec_ VehicleType$_{it}$***	***(Mis)FitElec_ Mileage$_{it}^{c}$***	***PctElecGeo Neighbors$_{it}$***	***Pct Restricted$_{it}$***	***Purchases$_{it}^{b}$***
Inc	Both (Mostly Inc)	0.00 (0.02)	0.04 (0.01)***	2.96 (0.05)***	-0.47 (0.02)***	1.17 (0.07)***	0.15 (0.02)***	0.79 (0.01)***
	Both (Mostly New)	-0.23 (0.03)***	0.08 (0.02)***	4.14 (0.14)***	-0.90 (0.07)***	1.66 (0.17)***	0.81 (0.04)***	0.12 (0.04)***
	New	-0.13 (0.02)***	0.18 (0.01)***	4.04 (0.11)***	-0.96 (0.05)***	2.04 (0.12)***	0.89 (0.03)***	-13.89 (0.23)***
Both (Mostly Inc)	Inc	0.02 (0.02)	-0.07 (0.02)***	-2.00 (0.09)***	0.25 (0.04)***	-0.75 (0.15)***	-0.34 (0.04)***	-0.77 (0.02)***
	Both (Mostly New)	-0.18 (0.02)***	0.04 (0.02)*	1.76 (0.14)***	-0.20 (0.06)**	0.85 (0.17)***	0.70 (0.04)***	-0.71 (0.03)***
	New	-0.32 (0.03)***	0.17 (0.02)***	2.30 (0.19)***	-0.25 (0.08)**	0.93 (0.20)***	1.04 (0.05)***	-13.90 (0.23)***
Both (Mostly New)	Inc	0.18 (0.05)***	0.02 (0.04)	-0.97 (0.26)***	-0.06 (0.10)	-0.98 (0.36)**	-0.62 (0.09)***	-7.86 (0.21)***
	Both (Mostly Inc)	0.20 (0.04)***	0.07 (0.03)*	-0.88 (0.19)***	-0.00 (0.07)	-0.96 (0.22)***	-0.28 (0.06)***	-0.27 (0.04)***
	New	-0.16 (0.03)***	0.15 (0.03)***	1.63 (0.19)***	-0.13 (0.07)	0.24 (0.21)	0.71 (0.06)***	-3.98 (0.09)***
New	Inc	0.55 (0.04)***	-0.15 (0.02)***	-2.98 (0.20)***	0.44 (0.07)***	-1.26 (0.29)***	-1.56 (0.07)***	-3.58 (0.23)***
	Both (Mostly Inc)	0.29 (0.04)***	0.01 (0.03)	-1.77 (0.21)***	0.32 (0.07)***	-0.94 (0.26)***	-1.02 (0.07)***	3.19 (0.13)***
	Both (Mostly New)	0.10 (0.03)**	-0.03 (0.02)	-0.74 (0.17)***	0.34 (0.06)***	-0.30 (0.19)	-0.49 (0.05)***	4.41 (0.10)***

Notes: Columns list the coefficient estimates (std. errors in parentheses) for each variable's effect on the probability of transitioning from the "From" to the "To" state relative to remaining in the "From" state (represented as the rows). Odds ratios can be calculated by exponentiating each coefficient. Coefficient estimates for time indicator variables are not shown. ***, **, and * indicate significance at the 0.001, 0.01, and 0.05 levels. [a,b,c] variables scaled by dividing by 10 (a), 100 (b), and 100,000 (c).

at *t*-1 and the 3 other states. Prior to model estimation, we scaled several variables by dividing them by multiples of 10 (as noted in Tables 3 and 5) so that all variables were of similar magnitude.

The results in Table 5 provide support for the nuanced effect of *ChannelHistory*$_{it}$ discussed above. *ChannelHistory*$_{it}$ has no significant influence on the Incumbent→Both (Mostly Inc) transition.[13] Furthermore, *ChannelHistory*$_{it}$ has a negative and significant influence on all other transitions to states involving a higher percentage of electronic purchasing (e.g., Incumbent→Both (Mostly New), Both (Mostly Inc)→Both (Mostly New), etc.). For example, a standard deviation increase in *ChannelHistory*$_{it}$ is associated with a 10.0% decrease in the odds of transitioning from Both (Mostly New) to New.[14] This indicates that channel history has minimal influence on an entity's transition to a limited level of electronic purchasing, but a negative influence on its transition to greater levels. Looking at transitions in the other direction, *ChannelHistory*$_{it}$ has a positive and significant influence on most transitions to states involving a lower percentage of electronic purchasing (the one exception being Both (Mostly Inc)→Incumbent). This indicates that entities with long channel histories are more likely than those with short channel histories to scale back or discontinue use of the new channel after adopting it. Put together, the results indicate that entities with long channel histories are more likely to follow an extension, retrenchment, or discontinuance pattern while entities with short channel histories are more likely to follow a replacement pattern.

The control variables are consistent with expectation and provide additional insight into dealers' channel transitions. Increased use of the electronic channel by a dealer's geographic neighbors is associated with transitions to states involving more electronic channel use. For example, a standard deviation increase in *PctElecGeo_Network*$_{it}$ increases the odds of an Incumbent→Both (Mostly Inc) transition by 9.8%. Higher transaction costs associated with using the physical channel, as reflected by a larger value for *DistanceClosest*

[13]In robustness checks (see appendix), this coefficient is sometimes positive and sometimes negative, but always small in magnitude.

[14]To arrive at these percentages, we multiplied a variable's coefficient by its standard deviation, and then exponentiated the result. For example, to calculate the 10.0%, we multiplied the *ChannelHistory*$_{it}$ coefficient for the Both (Mostly New) to New transition (-0.16) by the standard deviation of *Channel History*$_{it}$ (0.66). Exponentiating the result yields a value of 0.90, representing a 10% decrease in odds.

Facility$_{it}$, are also associated with transitions to states involving more electronic channel use. A standard deviation increase in *DistanceClosestFacility*$_{it}$ is associated with a 2.5% increase in the odds of an Incumbent→Both (Mostly Inc) transition and a 4.3% decrease in a Both (Mostly Inc)→ Incumbent transition. Better fit with the electronic channel has a similar, although larger, influence. A standard deviation increase in *FitElec_VehicleType*$_{it}$ increases the probability of an Incumbent→Both (Mostly Inc) transition by 115.7% and decreases the odds of a New→Both (Mostly New) transition by 17.6%. Also, a standard deviation increase in *(Mis)Fit Elec_Mileage*$_{it}$ decreases the odds of an Incumbent→ Both (Mostly Inc) transition by 19.0% and increases the odds of a New→Both (Mostly New) transition by 16.7%. Exposure to similar innovations, as reflected by *PctRestricted*$_{it}$, also positively influences transitions to states involving more electronic channel use.

The influence of *Purchases*$_{it}$ is worth discussing separately. Higher purchase volume increases the probability that a dealer will transition to (or stay in) one of the Both states. This differs from the other control variables, for which an increase (generally) drives a dealer to either the Incumbent or New states. This highlights the importance of accounting for the possibility that effects will vary based on a dealer's prior state (i.e., state dependence). To wit, an increase in *Purchases*$_{it}$ increases the probability that a dealer will transition to a higher percentage of electronic channel use if he was previously using only the incumbent channel. However, the same increase *decreases* the probability that a dealer will transition to a higher percentage of electronic channel use if he was previously using both channels.

Integrating and Extending the Prior Analyses

In our earlier analysis, we showed that entities that adopt at similar times follow different post-adoption channel use patterns. In this supplemental analysis, we leverage the mixed logit results to explore why. Figure 3 illustrates that dealers following the Gr1 (gradual replacement) and R1 (retrenchment) patterns had similar electronic purchasing trajectories up to Q204, after which their use patterns diverged dramatically. The mixed logit results suggest that dealers were more likely to continue increasing their level of electronic purchasing if (1) the transaction costs of using the physical channel were relatively high (i.e., high *DistanceClosest Facility*$_{it}$), (2) the fit of the electronic channel to their needs was high (i.e., *FitElec_VehicleType*$_{it}$ and low *(Mis)FitElec_ Mileage*$_{it}$), (3) their geographic neighbors increased their electronic purchasing (i.e., high *PctElecGeoNeighbors*$_{it}$), (4) they had high exposure to similar innovations (i.e., high *Pct Restricted*$_{it}$), and (5) they purchased relatively few vehicles (i.e., low *Purchases*$_{it}$). (Because the use patterns shown in Figure 3 are based on the dealers who purchased in all 25 quarters in the time period, *ChannelHistory*$_{it}$ does not vary in this analysis and hence we do not consider it here.) Figure 5 shows plots of the average values of *PctElec Purchases*$_{it}$ and the explanatory variables from Q204 to Q405 for dealers following the Gr1 and R1 patterns; we used Q204 because that is when the patterns diverged and Q405 because that is when the Gr1 pattern first reached 100% electronic purchasing. These results are consistent with the mixed logit results.

Specification and Robustness Checks

A potential problem with our analysis of the variables that influence dealers' new/incumbent channel use is reverse causality. We discuss each variable in turn. First, because a dealer's channel history is determined by when he first begins using the channels to purchase vehicles, his subsequent use cannot reverse cause *ChannelHistory*$_{it}$. Second, a dealer's use of the physical and electronic channels would only reverse cause his *DistanceClosest Facility*$_{it}$ if it caused him to relocate his dealership or caused a physical facility to open or close near his location, both of which are highly unlikely. Third, changes in a dealer's channel use could reverse cause *PctElec GeoNeighbors*$_{it}$ if the dealer influenced his geographic neighbors to use the electronic channel more or less. However, on average, each dealer purchased only 0.77% of the vehicles in his geographic network (st. dev.: 3.72%). Given this, it is more likely for the channel use behaviors of neighbors to influence the individual dealer (as we assume) than the other way around. Fourth, whether a dealer participates in restricted sales events is determined by whether the dealer has a relationship with the seller (e.g., is a franchisee). Because this is a fixed characteristic of the dealer, his channel use is unlikely to reverse cause *Pct Restricted*$_{it}$. Fifth, reverse causality is more plausible for the fit measures and for *Purchases*$_{it}$. It is possible that a dealer's transition from the Incumbent state to one involving electronic purchasing would (1) make him more likely to purchase the type of vehicles that were available electronically, or (2) cause him to purchase more vehicles, perhaps due to greater convenience of electronic purchasing. We believe both possibilities are unlikely because dealers are professional buyers who are procuring inventory; what and how much they purchase are likely to be determined by business considerations, not by the number of channels they use for procurement. Nevertheless, we conducted robustness checks to examine these possibilities. Both reverse causality concerns rely on dealers *changing* what and how much they purchased as a result of their adoption of the electronic channel. Our approach for the robustness checks was to identify and estimate the model using the subset of dealers who did *not* change what and how much they pur-

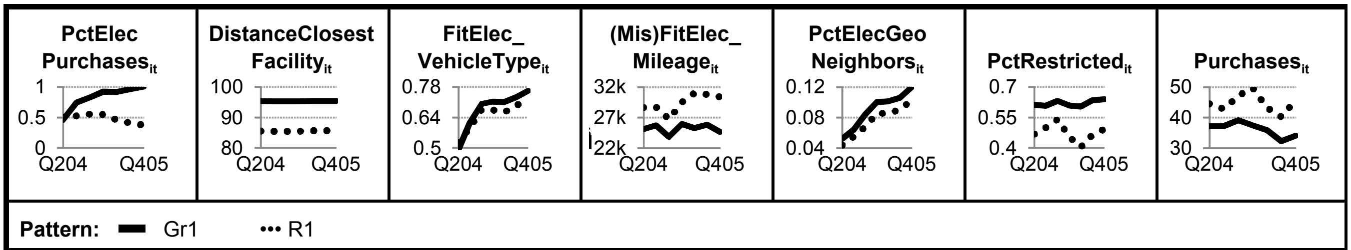


Figure 5. Average Values of Variables from Q204 to Q205 for Dealers Following the Gradual Replacement (GR1) and Retrenchment (R1) Patterns

chased (at least not appreciably) over the time span of the data. As discussed further in the appendix, the results of this analysis are consistent with those for the full sample, thereby mitigating the reverse causality concerns.

In the appendix, we discuss other potential issues and robustness checks. These include (1) potential heterogeneity in the buyers who purchase vehicles for dealer *i*, (2) classification of a dealer's state when the number of purchases in a quarter is low, and (3) potential mismeasurement of $ChannelHistory_{it}$.

Discussion

Contributions to Research and Practice

Technology adoption and innovation diffusion theory tends to focus on the innovation without considering the incumbent practice/technology/channel that it may replace. This is reflected in the pro-innovation bias of this literature. This bias may be inconsequential when studying the adoption of new products, as the act of adopting the new product often presumes discontinuing use of the incumbent product (e.g., when someone purchases a new smartphone or refrigerator). However, the bias can be harmful when studying other classes of innovations, such as new channels, because it causes the researcher to overlook the larger context in which the innovation diffuses.

We address this bias, and also contribute to research on the post-adoption use of innovations, by examining how use of a new channel relates to use of an incumbent channel over an extended time period. We show both conceptually and empirically that entities that adopt the new channel at similar times often follow different channel use patterns. This allows us to expand upon the traditional adopter categories (i.e., innovators, early adopters, etc.). Recognizing this heterogeneity within the traditional adopter categories is important for understanding and forecasting the new channel's diffusion. For example, suppose that some innovators follow a replacement pattern while others follow a retrenchment pattern. It is likely that further adoption of the new channel will come from entities that resemble the "innovators who replace" than from entities that resemble the "innovators who retrench." Recognizing heterogeneity in channel use of entities *across* adopter categories can also yield insight into the new channel's diffusion. For example, if most innovators follow a replacement pattern while most of the early majority follow an extension or retrenchment pattern, then it is likely that the new channel will be less appealing to later adopters.

We also contribute to the literature by analyzing factors associated with why an entity would follow a certain pattern of new/incumbent channel use. This means (for example) that we identify factors that would distinguish an "innovator who replaces" from an "innovator who retrenches." We focus on how an entity's channel history affects its transitions between new and incumbent channels. We find a nuanced effect in which channel history has minimal influence on entities' initial transitions from the incumbent channel to using both the incumbent and new channels (at least to a limited degree), but a significant (and negative) influence on entities' further transitions to a greater degree of new channel use. As a result, the longer (shorter) an entity's channel history, the more likely it is to follow an extension (replacement) pattern. We also document several other factors that affect entity's channel transitions, including how the channel fits an entity's needs, the transaction costs of using the channels, and how often an entity uses the functions that the channels provide. Although our empirical analysis is of a new and an incumbent purchasing channel, the findings apply more broadly to other channels. We also believe that our findings can inform analysis of channels that do not yet exist. For example, in the future, some adopters might use hologram-based communication to replace video chat, others might use two in conjunction, etc., with these changes determined by channel history, fit, etc.

Although none of the channel use patterns in our typology are new per se, we believe that classifying them as we have also contributes to research. Bailey (1994, p. 1) succinctly stated the importance of classification as follows: "Without classification, there could be no advanced conceptualization, reasoning, language, data analysis, or, for that matter, social science research." The patterns in the typology are applicable to multiple fields including information systems, medicine, education, marketing, and sociology. This can help to integrate the research on how new channels relate to incumbent channels across disciplines. This contributes to a cumulative research tradition, promotes knowledge transfer, and facilitates the comparison of findings across disciplines.

The research has implications for managers who must determine how to manage new channels and the incumbent channels that they may replace. These managers have an interest in knowing not only whether entities adopt new channels, but also whether they use them alongside or instead of incumbent channels and how quickly these behaviors evolve. This is because managers must know whether (and for whom) to support the incumbent channels. The typology, explanatory variables, and methods presented herein give managers tools to make sense of this. For example, managers can classify entities based on the patterns in the typology. The explanatory variables can help them understand why some entities follow one pattern while others follow another. They can also develop intervention strategies to stimulate optimal use patterns. To the extent that new channels generate welfare gains (e.g., Brynjolfsson et al. 2003), understanding how use patterns evolve and may be influenced can not only help individual firms but can also have public policy implications.

Limitations and Future Research

Our research has limitations that present opportunities for future research. For example, we do not study the consequences of the channel use patterns that we identify. It may be that some patterns lead to better outcomes for users, technology providers, or society. We also recognize that the explanatory variables that we have identified are unlikely to be exhaustive. Other variables may be identified as additional multiyear longitudinal studies of new and incumbent channel use are conducted in different contexts. Similarly, there may be other interesting channel use patterns that are not reflected in the typology, particularly for situations in which entities use both channels or only the new channel when they first adopt. We do not focus on these, in part to manage the scope of our analysis and in part because these situations are rare in the empirical context we use. Future research can build upon our work to examine other potential patterns of interest. Last, although we believe that reverse causality is unlikely in our empirical application and we have implemented robustness checks to examine it, we cannot strictly rule it out given our observational data.

Conclusion

Despite abundant research on entities' adoption and use of new channels, surprisingly little research addresses how use of a new channel relates to use of the incumbent channel that the new channel may or may not replace, particularly how this varies across adopting entities and over time. To address this gap, we examined how and why entities' use of new and incumbent channels evolves over time. We situated our analysis in the prior literature by deriving a typology of how channel use patterns evolve over time, which includes abrupt replacement, gradual replacement, extension, retrenchment, discontinuance (extension and replacement), and no adoption. We show that entities that adopt the new channel at similar times often follow dramatically different channel use patterns, which allows us to expand upon the traditional adopter categories (Rogers 2003). We also explore how entities' channel histories affect how they transition between new and incumbent channels. We find that entities with long and short channel histories are similarly likely to transition from using only the incumbent channel to using both channels, with entities with long channel histories more likely to continue using the incumbent channel at the same time. We draw upon the attitudes-motivation-capability framework (Chen and Miller 2012; Nan et al. 2014) to identify and test the influence of other explanatory factors, including the channel use behaviors of an entity's neighbors, the transaction costs of using the channels, how often an entity engages in the functions provided by the channels, how well the channels fit an entity's needs, and an entity's exposure to similar innovations.

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References

Angst, C. M., Agarwal, R., Sambamurthy, V., and Kelley, K. 2010. "Social Contagion and Information Technology Diffusion: The Adoption of Electronic Medical Records in U.S. Hospitals," *anagement Science* (56:8), pp. 1219-1241.

Ansari, A., Mela, C. F., and Neslin, S. A. 2008. "Customer Channel Migration," *Journal of Marketing Research* (45:1), pp. 60-76.
Bailey, K. D. 1994. *Typologies and Taxonomies: An Introduction to Classification Techniques* (1st ed.), Thousand Oaks, CA: Sage Publications.
Bala, H., and Venkatesh, V. 2015. "Adaptation to Information Technology: A Holistic Nomological Network from Implementation to Job Outcomes," *Management Science* (62:1), pp. 156-179.
Balasubramanian, S. 1998. "Mail Versus Mall: A Strategic Analysis of Competition between Direct Marketers and Conventional Retailers," *Marketing Science* (17:3), pp. 181-195.
Bapna, R., Goes, P., and Gupta, A. 2004. "User Heterogeneity and Its Impact on Electronic Auction Market Design: An Empirical Exploration," *MIS Quarterly* (28:1), pp. 21-43.
Bernard, R. M., Abrami, P. C., Lou, Y., Borokhovski, E., Wade, A., Wozney, L., Wallet, P. A., Fiset, M., and Huang, B. 2004. "How Does Distance Education Compare with Classroom Instruction? A Meta-Analysis of the Empirical Literature," *Review of Educational Research* (74:3), pp. 379-439.
Biyalogorsky, E., and Naik, P. 2003. "Clicks and Mortar: The Effect of Online Activities on Offline Sales," *Marketing Letters* (14:1), pp. 21-32.
Brynjolfsson, E., Hu, Y. J., and Smith, M. D. 2003. "Consumer Surplus in the Digital Economy: Estimating the Value of Increased Product Variety at Online Booksellers," *Management Science* (49:11), pp. 1580-1596.
Burns, L. R., and Wholey, D. R. 1993. "Adoption and Abandonment of Matrix Management Programs: Effects of Organizational Characteristics and Interorganizational Networks," *Academy of Management Journal* (36:1), pp. 106-138.
Chen, M., and Miller, D. 2012. "Competitive Dynamics: Themes, Trends, and a Prospective Research Platform," *Academy of Management Annals* (6:1), pp. 135-210.
Deutschmann, P. J., and Fals Borda, O. 1962. "Communication and Adoption Patterns in an Andean Village," Report, Programma Interamericano de Informacion Popular, San Jose, Costa Rica.
Devaraj, S., and Kohli, R. 2003. "Performance Impacts of Information Technology: Is Actual Usage the Missing Link?," *Management Science* (49:3), pp. 273-289.
Downes, L., and Nunes, P. 2013. "Big-Bang Disruption," *Harvard Business Review* (91:3), pp. 44-56.
Fichman, R. G. 2004. "Going Beyond the Dominant Paradigm for Information Technology Innovation Research: Emerging Concepts and Methods," *Journal of the AIS* (5:8), pp. 314-355.
Fisher, J., Kim, Y.-M., and Cummings, J. 2018. "Abandoning Innovations: Network Evidence on Enterprise Collaboration Software," in *Academy of Management Proceedings* (2018:1), G. Atinc (ed.) (https://doi.org/10.5465/AMBPP.2018.175).
Forman, C., Ghose, A., and Goldfarb, A. 2009. "Competition between Local and Electronic Markets: How the Benefit of Buying Online Depends on Where You Live," *Management Science* (55:1), pp. 47-57.
Genesove, D. 1993. "Adverse Selection in the Wholesale Used Car Market," *Journal of Political Economy* (101:4), pp. 644-665.
Gentzkow, M. 2007. "Valuing New Goods in a Model with Complementarity: Online Newspapers," *American Economic Review* (97:3), pp. 713-744.
Greenhalgh, T., Stramer, K., Bratan, T., Byrne, E., Russell, J., and Potts, H. W. W. 2010. "Adoption and Non-Adoption of a Shared Electronic Summary Record In England: A Mixed-Method Case Study," *British Medical Journal* (340), pp. c3111.
Greve, H. R. 2011. "Fast and Expensive: The Diffusion of a Disappointing Innovation," *Strategic Management Journal* (32:9), pp. 949-968.
Heffner, V. A., Lyon, V. B., Brousseau, D. C., Holland, K. E., and Yen, K. 2009. "Store-and-Forward Teledermatology Versus in-Person Visits: A Comparison in Pediatric Teledermatology Clinic," *Journal of the American Academy of Dermatology* (60:6), pp. 956-961.
Herhausen, D., Binder, J., Schoegel, M., and Herrmann, A., 2015. "Integrating Bricks with Clicks: Retailer-Level and Channel-Level Outcomes of Online–Offline Channel Integration," *Journal of Retailing* (91:2), pp. 309-325.
Hotelling, H. 1929. "Stability in Competition," *The Economic Journal* (39:153), pp. 41-57.
Howells, J., and Bessant, J. 2012. "Introduction: Innovation and Economic Geography: A Review and Analysis," *Journal of Economic Geography* (12:5) pp. 929-942.
Jeffers, P. I., and Nault, B. R. 2011. "Why Competition from a Multi-Channel E-Tailer Does Not Always Benefit Consumers," *Decision Sciences* (42:1), pp. 69-91.
Jeyaraj, A., and Rottman, J. W., and Lacity, M. C. 2006. "A Review of the Predictors, Linkages, and Biases in IT Innovation Adoption Research," *Journal of Information Technology* (21:1), pp. 1-23.
Joseph, R. C. 2010. "Individual Resistance to IT Innovations," *Communications of the ACM* (53:4), pp. 144-146.
Kotler, P. T., and Keller, K. L. 2016. *Marketing Management* (15th ed.), London: Pearson.
Langer, N., Forman, C., Kekre, S., and Sun, B. 2012. "Ushering Buyers into Electronic Channels: An Empirical Analysis," *Information Systems Research* (23:4), pp. 1212-1231.
Miles, R. E., and Snow, C. 1978. *Organizational Strategy, Structure and Process*, New York: McGraw Hill.
Miscione, G. 2007. "Telemedicine in the Upper Amazon: Interplay with Local Health Care Practices," *MIS Quarterly* (31:2), pp. 403-425.
Mohammed, S. 2001. "Personal Communication Networks and the Effects of an Entertainment-Education Radio Soap Opera in Tanzania," *Journal of Health Communication* (6:2), pp. 137-154.
Nan, N., Zmud, R., and Yetgin, E. 2014. "A Complex Adaptive Systems Perspective of Innovation Diffusion: An Integrated Theory and Validated Virtual Laboratory," *Computational and Mathematical Organization Theory* (20:1), pp. 52-88.
Neslin, S. A., and Shankar, V. 2009. "Key Issues in Multichannel Customer Management: Current Knowledge and Future Directions," *Journal of Interactive Marketing* (23:1), pp. 70-81.
Oberholzer-Gee, F., and Strumpf, K. 2007. "The Effect of File Sharing on Record Sales: An Empirical Analysis," *Journal of Political Economy* (115:1), pp. 1-42.
Overby, E., and Jap, S. 2009. "Electronic and Physical Market Channels: A Multiyear Investigation in a Market for Products of Uncertain Quality," *Management Science* (55:6), pp. 940-957.
Palen, T. E., Ross, C., Powers, J., and Xu, S. 2012. "Association of Online Patient Access to Clinicians and Medical Records with

Use of Clinical Services," *Journal of the American Medical Association* (308:19), pp. 2012-2019.

Polites, G. L., and Karahanna, E. 2012. "Shackled to the Status Quo: The Inhibiting Effects of Incumbent System Habit, Switching Costs, and Inertia on New System Acceptance," *MIS Quarterly* (36:1), pp. 21-42.

Polites, G. L., and Karahanna, E. 2013. "The Embeddedness of Information Systems Habits in Organizational and Individual Level Routines: Development and Disruption," *MIS Quarterly* (37:1), pp. 221-246.

Poole, M., and Van de Ven, A., 1989. "Using Paradox to Build Management and Organization Theories," *Academy of Management Review* (14:4), pp. 562-578.

Prince, J., and Greenstein, S. 2017. "Measuring Consumer Preferences for Video Content Provision via Cord Cutting Behavior," *Journal of Economics & Management Strategy* (26:2), pp. 293-317.

Robey, D., Ross, J. W., and Boudreau, M. C. 2002. "Learning to Implement Enterprise Systems: An Exploratory Study of the Dialectics of Change," *Journal of Management Information Systems* (19:1), pp. 17-46.

Rochet, J. C., and Tirole, J. 2003 "Platform Competition in Two-Sided Markets," *Journal of the European Economic Association* (1:4), pp. 990-1029.

Rogers, E. M. 2003. *Diffusion of Innovations* (5th ed.), New York: Free Press.

Ryan, B., and Gross, N. C. 1943. "The Diffusion of Hybrid Seed Corn in Two Iowa Communities," *Rural Sociology* (8:1) pp. 15-24.

Samuelson, W., and Zeckhauser, R. 1988. "Status Quo Bias in Decision Making," *Journal of Risk and Uncertainty* (1:1), pp. 7-59.

Simon, D. H., and Kadiyali, V. 2007. "The Effect of a Magazine's Free Digital Content on Its Print Circulation: Cannibalization or Complementarity?," *Information Economics and Policy* (19:3/4), pp. 344-361.

Sveiby, K.-E., Gripenberg, P., and Segercrantz, B. 2012. *Challenging the Innovation Paradigm*, Abingdon-on-Thames, UK: Routledge.

Sykes, T. A., and Venkatesh, V., 2017. "Explaining Post-Implementation Employee System Use and Friendship, Advice and Impeding Social Ties," *MIS Quarterly* (41:3), pp. 917-936.

Train, K. E. 2009. *Discrete Choice Methods with Simulation* (2nd ed.), Cambridge, UK: Cambridge University Press.

Valentini, S., Montaguti, E., and Neslin, S. A. 2011. "Decision Process Evaluation in Customer Channel Choice," *Journal of Marketing* (75:6), pp. 72-86.

Van den Bulte, C. 2000. "New Product Diffusion Acceleration: Measurement and Analysis," *Marketing Science* (19:4), pp. 366-380.

Venkatesh, V., Thong, Y. T., and Xu, X. 2012. "Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology," *MIS Quarterly* (36:1), pp. 157-178.

Viswanathan, S. 2005. "Competing across Technology-Differentiated Channels: The Impact of Network Externalities and Switching Costs," *Management Science* (51:3) pp. 483-496.

Wootton, R. 2012. "Twenty Years of Telemedicine in Chronic Disease Management—An Evidence Synthesis," *Journal of Telemedicine and Telecare* (18:4), pp. 211-220.

Xu, J., Forman, C., Kim, J. B., and Van Ittersum, K. 2014. "News Media Channels: Complements or Substitutes? Evidence from Mobile Phone Usage," *Journal of Marketing* (78:4), pp. 97-112.

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RESEARCH ARTICLE

HOW DO ADOPTERS TRANSITION BETWEEN NEW AND INCUMBENT CHANNELS?

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Appendix

Altering the Parameters Used to Derive the Typology

Three parameters govern the typology of channel use patterns: the number of states, the number of periods, and the state in the initial period. The typology shown in Table 1 is based on three states (Incumbent, Both, and New) and three periods (periods 1, 2, and 3), with entities in the Incumbent state in the initial period. Here, we describe the effect of adjusting each of the three parameters by (1) adding more time periods and states, and (2) allowing entities to be in a state other than Incumbent in the initial period.

Adding More Time Periods and States

Adding more periods and permuting across them is possible but, in general, does not yield substantially new patterns, while also causing the number of permutations to grow exponentially. For example, sequences of Inc→Inc→Inc→Both and Inc→Both→Both→Both are both examples of the extension pattern. Also, we suspect that in many empirical contexts, entities reach a stable point where they remain in the same state indefinitely. The typology is effective for capturing patterns that display this type of stability. For example, a pattern of Inc→Both→Inc→Both→New→New→New stabilizes at the end and is approximated by the gradual replacement pattern.

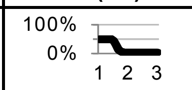
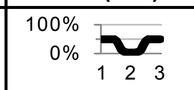
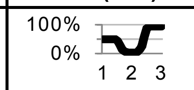
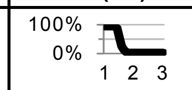
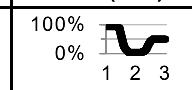
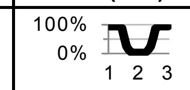
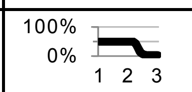
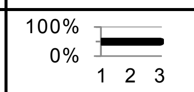
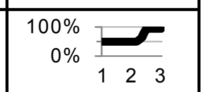
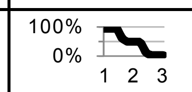
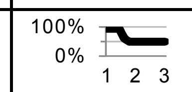
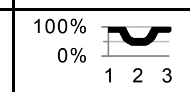
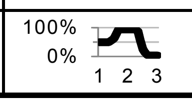
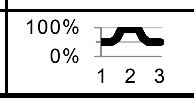
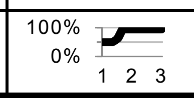
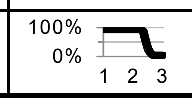
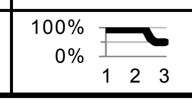
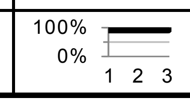
The Both state groups together entities whose percentage of new channel use relative to total use was both very low (but not 0%) and very high (but not 100%). For empirical applications (such as the one we investigate), it may be beneficial to divide the Both state into multiple substates that reflect different levels of new *vis-à-vis* incumbent use, such as a Both (Mostly Inc) and a Both (Mostly New) state. The patterns shown in Table 1 remain valid in this case. For example, a pattern of Inc→Both (Mostly Inc)→Both (Mostly New)→New fits the gradual replacement pattern, a pattern of Inc→Both (Mostly Inc)→Inc fits the discontinuance pattern, and a pattern of Inc→Both (Mostly New)→Both (Mostly Inc) fits the retrenchment pattern.

It is possible that additional patterns might be derived by adding more time periods and/or states. However, as articulated by Bailey (1994), a good typology must be detailed enough to capture relevant heterogeneity within a population, but not so detailed as to render the classification process moot (i.e., by creating a multiplicity of sparsely populated classes). We submit that the typology as derived strikes that balance. There is support for this in our empirical analysis: there are no major empirical patterns that are not represented by the typology.

Allowing Entities to Be in a State Other than Incumbent in the Initial Period

The typology shown in Table 1 assumes that entities are in the Incumbent state in time period 1. Table A1 shows versions of Table 1 in which entities are in the Both and New states in period 1. As is the case with adding more states, patterns shown in Table 1 remain evident, including Abrupt Replacement, Retrenchment, and Discontinuance (Extension and Replacement). Additional patterns also become evident, such as when an entity shifts from using both channels to using only the incumbent channel to using only the new channel. We do not focus on these additional patterns for the following reasons. First, cases in which entities are in the "Both" or "New" states in period 1 are quite rare in our empirical context, as noted in the "Empirical Validation of the Typology" section of the main text. Second, this helps us maintain the focus of the paper. Deeper exploration of these additional patterns in other contexts is an opportunity for future research.

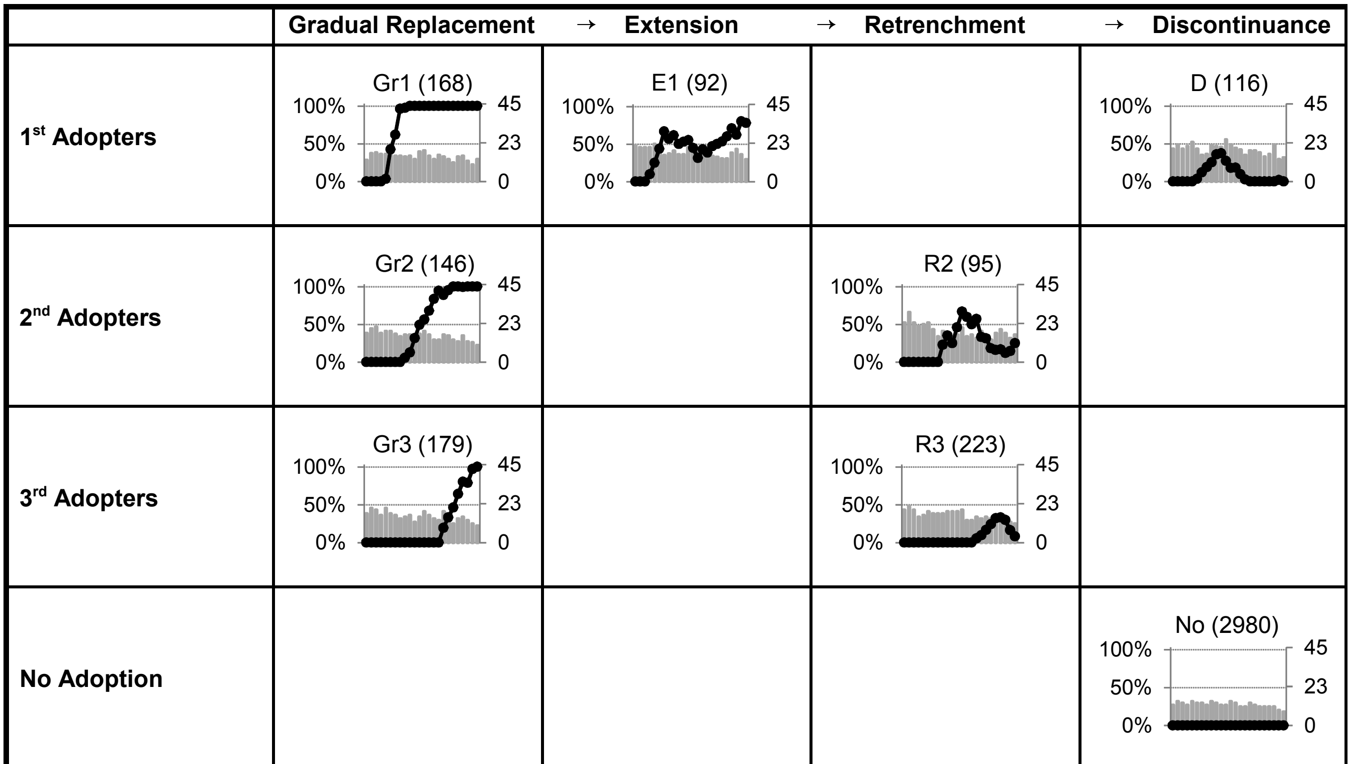
Table A1. Typology of New and Incumbent Channel Use Patterns When Entities' Initial State is "Both" or "New"

		State at Period 1 = "Both"					State at Period 1 = "New"		
		State at Period 3					State at Period 3		
		Inc ("I")	Both ("B")	New ("N")			Inc ("I")	Both ("B")	New ("N")
State at Period	I				State at Period	I			
	B					B			
	N					N			

Note: See Table 1 of the main text for a further description of this table.

Channel Use Patterns for Dealers Who Purchased in Fewer than 25 Quarters

As noted in the main text, we focused on dealers who made purchases in the 25 quarters contained in our data. Here, we consider whether our results are robust to including dealers who purchased in fewer quarters. First, we reran the cluster analysis for dealers who purchased in x quarters in our data, starting with $x = 24$ and progressively lowering x to 14. An issue with the cluster analysis for these dealers is that $PctElecPurchases_{it}$ is null for the quarters t in which they did not purchase (because its denominator is zero). To account for this, we "closed up" each dealer's *PctElecPurchases* array by dropping the null values. For example, if the *PctElecPurchases* array for dealer i was {0.2, 0.2, null, and 0.3} for the four quarters of 2003, we closed up the array to yield {0.2, 0.2, and 0.3}. Figure A1 shows the results of the cluster analysis for the dealers who purchased in $x = 24$ quarters. We determined the optimal number of clusters for this analysis to be 9, using the same procedure as in the main text. The use patterns are similar to those shown in the main text (see Figure 3). One difference is that there are fewer dealers following the extension and retrenchment patterns. This is likely because the dealers in this analysis had relatively low purchase volumes (on average), and the extension and retrenchment patterns are typical of dealers with high purchase volumes. Similar results hold for different values of x.



Note: See Figure 3 of the main text for a description of the plots.

Figure A1. New and Incumbent Technology Use Patterns from the k-Means Cluster Analysis for Dealers Who Purchased in 24 Quarters of the Data

The advantages of the closing up procedure are that it preserves the temporal order of each dealer's behavior and it eliminates the need to impute values for observations when $PctElecPurchases_{it}$ is null. A disadvantage is that if a dealer waits several quarters between purchases, then the closing up procedure will obscure this gap. To explore this, we reran the cluster analysis for each value of x (from $x = 14$ to $x = 24$) for only those dealers with no gaps in their purchasing behavior. Results remain consistent.

Mixed Logit Results for Dealers Who Purchased in All 25 Quarters of the Sample Period

As noted in the main text, we ran the mixed logit model for only those dealers who purchased in each of the 25 quarters of the sample time period. Table A2 shows the results.

Table A2. Results of Mixed Logit Model to Examine Dealer Transitions Between States of Electronic and Physical Channel Use

State Transitions							
From	**To**	***DistanceClosest Facility***$_{it}^{b}$	***FitElec_Vehicle Type***$_{it}$	***(Mis)FitElec_ Mileage***$_{it}^{c}$	***PctElecGeo Neighbors***$_{it}$	***Pct Restricted***$_{it}$	***Purchases***$_{it}^{b}$
Inc	Both (L)	0.08 (0.01)***	2.80 (0.09)***	-0.74 (0.04)***	0.56 (0.13)***	0.01 (0.03)	0.39 (0.01)***
	Both (H)	0.19 (0.04)***	4.06 (0.35)***	-1.86 (0.20)***	1.23 (0.34)***	0.46 (0.09)***	-0.94 (0.11)
	New	0.25 (0.07)***	6.51 (0.66)***	-0.76 (0.34)*	0.00 (0.60)	0.82 (0.15)***	-12.72 (0.79)***
Both (L)	Inc	-0.11 (0.02)***	-2.27 (0.16)***	0.09 (0.06)	-0.44 (0.16)**	0.08 (0.04)†	-0.43 (0.02)***
	Both (H)	0.08 (0.02)**	2.16 (0.28)***	-0.32 (0.13)*	0.54 (0.19)**	0.52 (0.06)***	-0.74 (0.04)***
	New	0.08 (0.06)**	4.10 (0.69)***	-0.47 (0.35)	0.26 (0.43)	1.17 (0.13)***	-9.06 (0.39)***
Both (H)	Inc	-0.03 (0.08)	-1.12 (0.57)*	0.04 (0.23)	-1.94 (0.59)***	-0.32 (0.14)*	-5.85 (0.31)***
	Both (L)	0.12 (0.04)	-0.72 (0.36)*	-0.13 (0.15)	-1.29 (0.28)***	-0.14 (0.08)†	-0.31 (0.04)***
	New	0.11 (0.05)**	1.63 (0.50)**	-0.67 (0.23)**	0.13 (0.30)	0.56 (0.09)***	-2.25 (0.11)***
New	Inc	-0.21 (0.13)*	-0.81 (0.97)	1.74 (0.42)***	-0.40 (0.83)	-1.27 (0.22)***	-3.70 (0.58)***
	Both (L)	0.13 (0.08)	-0.72 (0.84)	1.41 (0.40)***	-0.75 (0.55)	-0.94 (0.16)***	1.39 (0.19)***
	Both (H)	-0.13 (0.06)*	-1.71 (0.60)**	0.55 (0.30)†	0.11 (0.36)	-0.58 (0.11)***	1.87 (0.13)***

Notes: Columns list the coefficient estimates (std. errors in parentheses) for each variable's effect on the probability of transitioning from the "From" to the "To" state relative to remaining in the "From" state (represented as the rows.) Odds ratios can be calculated by exponentiating each coefficient. Coefficient estimates for 23 time dummies are not shown. ***, **, *, and † indicate significance at the 0.001, 0.01, 0.05, and 0.10 levels. [a,b,c]Variables scaled by dividing by 100 (b) and 100,000 (c). *ChannelHistory*$_{it}$ withheld because it does not vary for dealers in the subsample used for this analysis.
The table includes only those dealers who purchased in each of the 25 quarters in the time span of the study (see the "Model Estimation and Results" section of the main text).

Potential Heterogeneity in the Buyers Who Purchase Vehicles for Dealer i

In our analysis, the unit of analysis is the dealer/quarter. Used car dealers are typically organizations with multiple employees, one or more of whom purchase vehicles in the wholesale market. Thus, the channel use behaviors of each dealer are determined by the behaviors of one or more employees. This means that some of the variation in channel use between dealers (as well as within a dealer over time) could be driven by the (unobserved) preferences of the employees who make the purchases, to whom we will refer as a dealer's *buyers*. We do not believe that the possibility of multiple buyers per dealer represents a serious threat to our findings because the channel use behaviors of dealer *i*'s buyers should be similar. First, buyers do not enjoy complete discretion over which channels to use; some of this is determined at the dealer level. For example, each buyer's ability to use the physical (electronic) channel is constrained by the dealer's travel budget (broadband connectivity). This will engender similarity in channel use by buyers within the same dealer. Second, the explanatory variables that influence a buyer's channel use are consistent across all buyers at dealer *i*; ergo, their channel use behaviors are likely to be consistent. The geographic variables, *DistanceClosestFacility*$_{it}$ and *PctElec_GeoNeighbors*$_{it}$, are identical across dealer *i*'s buyers. *FitElec_VehicleType*$_{it}$ and *(Mis)FitElec_Mileagei*$_{it}$ are consistent across dealer *i*'s buyers because each buyer purchases vehicles that meet the profile of dealer *i*'s business (in terms of vehicles' make/model, mileage, etc.) *Purchases*$_{it}$ and *PctRestricted*$_{it}$ are consistent across buyers because they are functions of a dealer's size and relationships with sellers, as opposed to being defined at the buyer level. Despite this, it remains possible that unobserved buyer level characteristics influence a dealer's channel use. However, because these characteristics are aggregated to the dealer-level and distributed across thousands of dealers, they may "wash out" in our analysis.

Robustness Check: Estimating the Mixed Logit Model Using All Observations in an Omnibus Model and Accounting for Potential Mismeasurement of ChannelHistory$_{it}$

In our focal approach, we estimated the mixed logit model in stages that correspond to the dealer's state at time *t*-1. We also estimated an omnibus model in which we included all of a dealer's observations (regardless of his state at time *t*-1). By including all of a dealer's observations in a single model, we can better account for dealers' unobserved channel preferences, which we model via the normally distributed random intercepts for each state (α_{is}). Another potential issue is mismeasurement of *ChannelHistory*$_{it}$. Because our earliest observations are from Q1-2003, we code all dealers who purchased in Q1-2003 as having the same channel history. However, some of these dealers' channel histories could go back several years, whereas others could go back only a few quarters. To account for this, we identified the subset of dealers whose first observed purchase occurred in 2004 or later. This provides at least a one year buffer to ensure that dealers were not using the channels before we observe them to. We addressed these two issues simultaneously by estimating the omnibus model using this subset of dealers. We did this for the following reason. To account for state dependence in the omnibus model, we interacted each of the explanatory variables with a dummy variable representing the dealer's state in the prior period. This increased the model's dimensionality considerably, making convergence difficult, particularly given the large number of observations. By using the subset of dealers whose first observed purchased occurred after 2003, we limited the number of observations to include in the model, facilitating model convergence. (We also ran the omnibus model on a 12% random sample of the full data, achieving similar results.) Furthermore, given the large number of explanatory variables in the omnibus model (due primarily to all of the interactions), we did not include the (numerous) time indicator variables in the model. Instead, we used a linear time variable, which allowed us to control for effects due to the passage of time (e.g., improvements to the functionality and reliability of the electronic channel) without substantially increasing the model's dimensionality. Results are shown in Table A3. They are similar to those reported in the main text, although some of the coefficient estimates that are statistically significant in the focal model are insignificant in the omnibus model, perhaps due to the smaller sample size. In the main text, we focus on the results from separate stage models because they are based on the full data set and we are able to model time using yearly indicator variables, which is more flexible (and we believe more correct) than modeling time as a linear variable.

Table A3. Results of Mixed Logit Model Estimated in an Omnibus Fashion, Using Observations for Dealers Who First Observed Purchase Occurred after 2003

State Transitions		*Channel*	*DistanceClosest*	*FitElec_*	*(Mis)FitElec_*	*PctElecGeo*		
From	**To**	*$History_{it}^{a}$*	*$Facility_{it}^{b}$*	*$VehicleType_{it}$*	*$Mileage_{it}^{c}$*	*$Neighbors_{it}$*	*Pct $Restricted_{it}$*	*$Purchases_{it}^{b}$*
Inc	Both (Mostly Inc)	-0.04 (0.02)†	0.06 (0.02)**	1.36 (0.08)***	-1.06 (0.03)***	1.30 (0.16)***	-0.07 (0.05)	1.09 (0.03)***
	Both (Mostly New)	-0.18 (0.07)**	0.03 (0.04)	0.63 (0.18)***	-2.08 (0.09)***	2.47 (0.36)***	0.79 (0.10)***	0.24 (0.11)*
	New	-0.05 (0.05)	0.14 (0.02)****	1.11 (0.13)***	-2.18 (0.07)***	2.57 (0.24)***	1.07 (0.07)***	-16.58 (0.55)***
Both (Mostly Inc)	Inc	0.03 (0.04)	-0.06 (0.03)†	-4.11 (0.12)***	-0.58 (0.05)***	-0.42 (0.25)†	0.19 (0.08)*	-1.09 (0.05)***
	Both (Mostly New)	0.04 (0.06)	0.06 (0.04)***	0.32 (0.19)†	-0.32 (0.08)**	0.73 (0.33)*	0.68 (0.10)***	-0.99 (0.07)***
	New	-0.13 (0.07)†	0.19 (0.04)	0.36 (0.24)	-0.68 (0.10)***	1.18 (0.40)**	1.23 (0.12)***	-16.71 (0.57)***
Both (Mostly New)	Inc	0.32 (0.10)**	-0.05 (0.07)	-4.55 (0.31)***	1.00 (0.13)***	-0.67 (0.61)	-0.64 (0.17)***	-9.96 (0.50)***
	Both (Mostly Inc)	-0.03 (0.08)	0.04 (0.05)	-1.42 (0.24)***	-0.07 (0.07)	-0.32 (0.42)	0.27 (0.13*)	-0.66 (0.1)***
	New	0.00 (0.07)	0.11 (0.04)*	-1.00 (0.24)***	-0.54 (0.10)***	0.93 (0.37)*	0.83 (0.12)***	-4.09 (0.19)***
New	Inc	0.46 (0.07)***	-0.13 (0.04)**	-3.81 (0.19)***	-0.09 (0.08)	-1.39 (0.40)***	-1.0 (0.12)***	-3.58 (0.42)***
	Both (Mostly Inc)	0.06 (0.08)	-0.06 (0.04)	-1.78 (0.24)***	0.25 (0.09)***	-1.25 (0.43)**	-0.91 (0.13)***	3.35 (0.23)***
	Both (Mostly New)	-0.08 (0.07)	-0.02 (0.03)	-0.86 (0.21)***	0.39 (0.07)***	-0.47 (0.32)	-0.66 (0.10)***	4.34 (0.19)***

Columns list the coefficient estimates (std. errors in parentheses) for each variable's effect on the probability of transitioning from the "From" to the "To" state relative to remaining in the "From" state (represented as the rows.) Odds ratios can be calculated by exponentiating each coefficient. Coefficient estimates for linear time trends are not shown. ***, **, *, and † indicate significance at the 0.001, 0.01, 0.05, and 0.10 levels. [a,b,c]Variables scaled by dividing by 10 (a), 100 (b), and 100,000 (c).

Robustness Check: Potential Reverse Causality

As noted in the main text, we explored potential reverse causality with respect to the fit measures and $Purchases_{it}$ by estimating the model on the subset of dealers who did *not* change what and how much they purchased (at least not appreciably) over the time span of our data. For this analysis, we used the dealers who purchased in each of the 25 quarters in the data. By using these dealers, we had enough data points to assess whether each dealer was behaving consistently over time. Also, as shown in Table A2, results for these dealers are similar to those for the full sample. We examined reverse causality with respect to fit by measuring the consistency (or lack thereof) in the types of vehicles purchased by each of these dealers over the 25 quarters in the data. We did this in two ways. First, we identified which make of vehicle (e.g., Ford, Toyota) each dealer *i* purchased the most of in each quarter *t*, which we labeled $ModeMake_{it}$, along with the percentage of dealer *i*'s purchases in quarter *t* that were of this modal make ($ModeMakePercent_{it}$). There were 2,633 dealers (who purchased 3,335,552 total vehicles) who had the same $ModeMake_{it}$ in at least 24 of the 25 quarters, that is, who consistently purchased a relatively large number of vehicles of the same make each quarter (the average $ModeMakePercent_{it}$ for these dealers was 71.3%.) We reran the analysis for this subset; results appear in Table A4.[1]

[1]Conducting the analysis using this subset means that the $FitElec\_VehicleType_{it}$, $(Mis)FitElec\_Mileage_{it}$, and $Purchases_{it}$ coefficients are identified (mostly) based on differences across dealers rather than changes within each dealer over time.

Table A4. Results of Mixed Logit Model to Examine Dealer Transitions Between States of Electronic and Physical Channel Use

State Transitions		DistanceClosest	FitElec_	(Mis)FitElec_	PctElecGeo		
From	To	$Facility_{it}^{b}$	$VehicleType_{it}$	$Mileage_{it}^{c}$	$Neighbors_{it}$	Pct $Restricted_{it}$	$Purchase_{it}^{b}$
Inc	Both (L)	0.14 (0.03)***	2.08 (0.18)***	-0.84 (0.11)***	1.13 (0.25)***	-0.07 (0.05)	0.46 (0.02)***
	Both (H)	0.32 (0.09)***	3.80 (0.58)***	-2.11 (0.56)****	1.18 (0.63)†	0.04 (0.17)	-0.81 (0.18)***
	New	0.26 (0.15)†	5.73 (1.07)***	-2.32 (1.17)†	-1.33 (1.29)	0.40 (0.30)	-11.09 (1.14)***
Both (L)	Inc	-0.21 (0.04)***	-1.09 (0.32)**	0.33 (0.17)†	-0.78 (0.31)**	-0.07 (0.07)	-0.50 (0.04)***
	Both (H)	0.08 (0.05)†	0.95 (0.49)†	-0.59 (0.32)	0.13 (0.34)	0.52 (0.10)***	-0.97 (0.07)***
	New	-0.05 (0.11)	3.87 (1.26)**	-0.89 (0.91)	0.78 (0.68)	1.00 (0.25)***	-7.79 (0.55)***
Both (H)	Inc	-0.21 (0.15)	-2.37 (1.15)*	0.53 (0.63)	-1.92 (1.50)†	-0.44 (0.26)†	-4.97 (0.47)***
	Both (L)	0.13 (0.07)†	0.41 (0.64)	0.25 (0.35)	-1.82 (0.49)***	-0.24 (0.14)†	-0.29 (0.09)**
	New	0.07 (0.08)	1.99 (0.86)*	-1.95 (0.59)**	0.27 (0.51)	0.46 (0.17)**	-2.45 (0.18)***
New	Inc	-0.75 (0.31)**	-1.54 (2.08)	1.11 (1.40)	-0.08 (1.85)	-0.66 (0.45)	-3.91 (1.04)***
	Both (L)	0.16 (0.15)	-1.39 (1.47)	3.56 (0.90)***	-1.11 (0.93)	-0.43 (0.29)	1.26 (0.29)***
	Both (H)	-0.27 (0.10)**	-1.79 (0.99)†	0.98 (0.70)	0.96 (0.55)†	-0.38 (0.19)*	1.67 (0.19)***

Notes: Columns list the coefficient estimates (std. errors in parentheses) for each variable's effect on the probability of transitioning from the "From" to the "To" state relative to remaining in the "From" state (represented as the rows.) Odds ratios can be calculated by exponentiating each coefficient. Coefficient estimates for 23 time dummies are not shown. ***, **, *, and † indicate significance at the 0.001, 0.01, 0.05, and 0.10 levels.
[a,b,c]Variables scaled by dividing by 100 (b) and 100,000 (c). $ChannelHistory_{it}$ withheld because it does not vary for dealers in the subsample used for this analysis
The table includes only those dealers whose $ModeMake_{it}$ was the same in at least 24 of the 25 quarters.

Second, we computed the standard deviation of $(Mis)FitElec\_Mileage_{it}$ across the quarters in which dealer *i* purchased. This allowed us to measure the consistency in the average mileage of the vehicles purchased by each dealer over time. We reran the analysis for the subset of dealers for whom this standard deviation was relatively low (in the bottom tertile); see Table A5.

Table A5. Results of Mixed Logit Model to Examine Dealer Transitions Between States of Electronic and Physical Channel Use

State Transitions		DistanceClosest	FitElec_	(Mis)FitElec_	PctElecGeo	Pct	
From	To	$Facility_{it}^{b}$	$VehicleType_{it}$	$Mileage_{it}^{c}$	$Neighbors_{it}$	$Restricted_{it}$	$Purchases_{it}^{b}$
Inc	Both (L)	0.15 (0.02)***	2.49 (0.15)***	-0.56 (0.10)***	0.46 (0.19)**	-0.12 (0.04)**	0.23 (0.01)***
	Both (H)	0.17 (0.07)*	3.95 (0.52)***	-2.79 (0.57)***	1.32 (0.51)*	0.31 (0.14)*	-0.52 (0.13)***
	New	0.26 (0.12)*	3.32 (1.11)**	-2.68 (1.31)*	-2.13 (1.89)	0.78 (0.30)**	-8.97 (0.99)***
Both (L)	Inc	-0.08 (0.03)**	-1.41 (0.25)***	0.60 (0.16)***	-1.00 (0.22)***	0.17 (0.05)**	-0.27 (0.02)***
	Both (H)	0.05 (0.03)†	2.06 (0.42)***	-1.71 (0.33)***	0.44 (0.25)	0.41 (0.08)***	-0.54 (0.05)***
	New	-0.03 (0.09)	3.55 (1.14)**	-1.37 (0.92)	0.05 (0.58)	1.01 (0.20)***	-6.88 (0.43)***
Both (H)	Inc	-0.23 (0.13)†	1.54 (1.11)	2.21 (0.81)**	-3.10 (0.98)**	0.12 (0.22)	-4.56 (0.41)***
	Both (L)	0.13 (0.05)**	0.14 (0.58)	0.20 (0.41)	-1.63 (0.38)***	-0.18 (0.11)†	-0.28 (0.05)***
	New	0.07 (0.06)	2.97 (0.79)**	-1.25 (0.61)*q	0.44 (0.41)	0.66 (0.14)***	-1.83 (0.13)***
New	Inc	-0.17 (0.22)	-1.67 (1.95)	1.17 (1.51)	-1.92 (1.48)	-0.97 (0.38)**	-2.98 (0.84)***
	Both (L)	0.05 (0.13)	1.07 (1.53)	1.53 (1.04)	-0.60 (0.79)	-0.91 (0.25)***	1.08 (0.25)***
	Both (H)	-0.05 (0.08)	-0.38 (0.95)	-0.99 (0.70)	-0.20 (0.46)	-0.76 (0.16)***	1.76 (0.15)***

Notes: Columns list the coefficient estimates (std. errors in parentheses) for each variable's effect on the probability of transitioning from the "From" to the "To" state relative to remaining in the "From" state (represented as the rows.) Odds ratios can be calculated by exponentiating each coefficient. Coefficient estimates for 23 time dummies are not shown. ***, **, *, and † indicate significance at the 0.001, 0.01, 0.05, and 0.10 levels.
[a,b,c]Variables scaled by dividing by 100 (b) and 100,000 (c). $ChannelHistory_{it}$ withheld because it does not vary for dealers in the subsample used for this analysis.
The table includes only those dealers whose standard deviation of $(Mis)FitElec\_Mileage_{it}$ across the 25 quarters was in the bottom tertile.

We examined reverse causality with respect to purchases by measuring the consistency (or lack thereof) in the number of vehicles purchased by each dealer per quarter. We used an analogous process to identify those dealers for whom the standard deviation of $Purchases_{it}$ across the quarters in which he purchased was relatively low (in the bottom tertile). The results appear in Table A6. The results are generally consistent with the main result, which supports the direction of causality implied in our main analysis.

Table A6. Results of Mixed Logit Model to Examine Dealer Transitions Between States of Electronic and Physical Channel Use

State Transitions							
From	**To**	***DistanceClosestFacility***$_{it}^{b}$	***FitElec_VehicleType***$_{it}$	***(Mis)FitElec_Mileage***$_{it}^{c}$	***PctElecGeoNeighbors***$_{it}$	***PctRestricted***$_{it}$	***Purchases***$_{it}^{b}$
Inc	Both (L)	0.12 (0.03)***	2.90 (0.21)***	-0.74 (0.09)***	0.23 (0.23)	0.07 (0.06)	3.84 (0.16)***
	Both (H)	0.23 (0.06)***	3.28 (0.63)***	-1.23 (0.32)***	1.06 (0.56)†	0.63 (0.17)***	-6.96 (0.85)***
	New	0.27 (0.09)**	6.24 (0.96)***	-0.42 (0.47)	0.03 (0.94)	0.81 (0.25)**	-28.60 (2.75)***
Both (L)	Inc	-0.18 (0.04)**	-1.87 (0.33)***	0.32 (0.13)*	-0.61 (0.34)†	0.29 (0.09)**	-5.49 (0.28)***
	Both (H)	-0.04 (0.06)	1.39 (0.56)*	-0.12 (0.24)	0.61 (0.44)	0.58 (0.13)***	-5.90 (0.47)***
	New	-0.08 (0.12)	3.10 (1.06)**	0.04 (0.47)	1.28 (0.79)	1.04 (0.24)***	-23.61 (1.61)***
Both (H)	Inc	0.03 (0.14)	-2.29 (0.98)*	0.71 (0.35)*	-1.54 (0.99)	-0.57 (0.27)*	-14.17 (1.40)***
	Both (L)	0.07 (0.09)	-0.88 (0.74)	0.64 (0.28)*	-1.28 (0.60)*	0.44 (0.18)**	-0.53 (0.61)
	New	0.21 (0.10)*	0.70 (0.91)	-0.75 (0.39)†	1.50 (0.61)*	0.81 (0.19)***	-8.41 (0.80)***
New	Inc	0.01 (0.22)	-0.68 (1.63)	2.62 (0.66)***	-0.26 (1.39)	-0.98 (0.41)*	-15.03 (2.86)***
	Both (L)	-0.04 (0.17)	0.58 (1.57)	2.37 (0.63)***	-0.46 (1.06)	-0.88 (0.32)**	3.81 (1.27)**
	Both (H)	-0.18 (0.11)	-2.45 (1.01)*	0.60 (0.47)	-0.29 (0.66)	-0.87 (0.20)***	6.32 (0.78)***

Notes: Columns list the coefficient estimates (std. errors in parentheses) for each variable's effect on the probability of transitioning from the "From" to the "To" state relative to remaining in the "From" state (represented as the rows.) Odds ratios can be calculated by exponentiating each coefficient. Coefficient estimates for 23 time dummies are not shown. ***, **, *, and † indicate significance at the 0.001, 0.01, 0.05, and 0.10 levels.
[a,b,c]variables scaled by dividing by 100 (b) and 100,000 (c). $ChannelHistory_{it}$ withheld because it does not vary for dealers in the subsample used for this analysis.
The table includes only those dealers whose standard deviation of $Purchases_{it}$ across the 25 quarters was in the bottom tertile.

Robustness Check Regarding Minimum Number of Purchases per Quarter

As noted in the main text, we define the states based on the percentage of electronic purchases. Because this is a percentage, dealer-quarters with low numbers of purchases (the denominator of the percentage) could result in large changes in the percentage with relatively small changes in the numerator. To limit the concern that this could affect the results, we reran the mixed logit model after removing observations in which dealers made fewer than x purchases in quarter t or quarter t-1, setting $x = 5$ and $x = 10$. Results are similar to the focal results and are shown in Tables A7 and A8.

Table A7. Results of Mixed Logit Model to Examine Dealer Transitions Between States of Electronic and Physical Channel Use

State Transitions		*Channel History*$_{it}^{a}$	*DistanceClosest Facility*$_{it}^{b}$	*FitElec_ VehicleType*$_{it}$	*(Mis)FitElec_ Mileage*$_{it}^{c}$	*PctElecGeo Neighbors*$_{it}$	*Pct Restricted*$_{it}$	*Purchases*$_{it}^{b}$
From	**To**							
Inc	Both (Mostly Inc)	0.05 (0.02)*	0.03 (0.02)	3.74 (0.07)***	-0.70 (0.04)***	1.48 (0.16)***	-0.17 (0.04)***	0.61 (0.02)***
	Both (Mostly New)	-0.40 (0.05)***	0.11 (0.03)***	4.98 (0.23)***	-1.27 (0.14)***	2.44 (0.32)***	0.43 (0.08)***	-0.27 (0.09)**
	New	-0.46 (0.08)***	0.23 (0.04)***	5.43 (0.40)***	-2.52 (0.30)***	2.17 (0.43)***	0.88 (0.12)***	-5.98 (0.42)***
Both (Mostly Inc)	Inc	0.07 (0.02)**	-0.09 (0.02)***	-2.27 (0.10)***	0.24 (0.04)***	-0.89 (0.16)***	-0.22 (0.04)***	-0.50 (0.02)***
	Both (Mostly New)	-0.17 (0.03)***	0.04 (0.02)	2.09 (0.16)***	-0.22 (0.07)**	0.87 (0.18)***	0.74 (0.05)***	-0.73 (0.03)
	New	-0.34 (0.05)***	0.18 (0.03)***	4.00 (0.38)***	-0.42 (0.18)*	0.96 (0.31)**	1.50 (0.09)***	-7.66 (0.23)***
Both (Mostly New)	Inc	0.29 (0.08)***	0.08 (0.05)	-1.01 (0.40)*	-0.27 (0.16)	-1.27 (0.47)**	-0.62 (0.12)***	-4.77 (0.22)***
	Both (Mostly Inc)	0.26 (0.04)***	0.08 (0.03)*	-1.13 (0.22)***	-0.02 (0.09)	-0.96 (0.25)***	-0.32 (0.07)***	-0.21 (0.04)***
	New	-0.12 (0.04)**	0.16 (0.03)***	2.41 (0.25)***	-0.04 (0.09)	0.07 (0.24)	0.86 (0.07)***	-2.70 (0.09)***
New	Inc	0.29 (0.12)*	0.12 (0.07)	-2.28 (0.71)**	-1.04 (0.37)**	-2.07 (0.70)**	-1.94 (0.18)***	-1.08 (0.37)**
	Both (Mostly Inc)	0.39 (0.08)***	0.10 (0.05)	-1.49 (0.52)**	0.40 (0.21)	-0.61 (0.44)	-1.37 (0.13)***	1.98 (0.18)***
	Both (Mostly New)	0.06 (0.04)	-0.02 (0.03)	-0.94 (0.31)**	0.62 (0.12)**	-0.28 (0.25)	-0.69 (0.07)***	2.64 (0.11)***

Notes: Columns list the coefficient estimates (std. errors in parentheses) for each variable's effect on the probability of transitioning from the "From" to the "To" state relative to remaining in the "From" state (represented as the rows.) Odds ratios can be calculated by exponentiating each coefficient. Coefficient estimates for time indicators are not shown. ***, **, and * indicate significance at the 0.001, 0.01, and 0.05 levels.
[a,b,c]variables scaled by dividing by 10 (a), 100 (b), and 100,000 (c).
The table excludes observations in which dealers made fewer than five purchases in quarter *t* or quarter *t*

Table A8. Results of Mixed Logit Model to Examine Dealer Transitions Between States of Electronic and Physical Channel Use

State Transitions		*Channel History*$_{it}^{a}$	*DistanceClosest Facility*$_{it}^{b}$	*FitElec_ VehicleType*$_{it}$	*(Mis)FitElec_ Mileage*$_{it}^{c}$	*PctElecGeo Neighbors*$_{it}$	*Pct Restricted*$_{it}$	*Purchases*$_{it}^{b}$
From	**To**							
Inc	Both (Mostly Inc)	0.07 (0.02)***	0.05 (0.02)**	3.91 (0.07)***	-0.74 (0.03)***	1.53 (0.15)***	-0.14 (0.03)***	0.49 (0.01)***
	Both (Mostly New)	-0.38 (0.05)***	0.13 (0.04)***	5.15 (0.22)***	-1.32 (0.14)***	2.35 (0.34)***	0.64 (0.08)***	-0.28 (0.08)***
	New	-0.23 (0.12)	0.25 (0.05)***	4.93 (0.51)***	-3.90 (0.49)***	2.61 (0.51)***	0.67 (0.16)***	-5.02 (0.46)***
Both (Mostly Inc)	Inc	0.07 (0.02)**	-0.09 (0.02)***	-2.40 (0.12)***	0.27 (0.05)***	-1.03 (0.18)***	-0.17 (0.04)***	-0.36 (0.02)***
	Both (Mostly New)	-0.17 (0.03)***	0.06 (0.02)*	2.36 (0.19)***	-0.30 (0.09)***	0.97 (0.21)***	0.86 (0.05)***	-0.58 (0.04)***
	New	-0.33 (0.08)***	0.15 (0.04)***	4.62 (0.59)***	-1.05 (0.32)**	0.75 (0.39)	1.40 (0.13)***	-5.30 (0.26)***
Both (Mostly New)	Inc	0.48 (0.12)***	0.09 (0.08)	-0.97 (0.60)	-0.41 (0.25)	-1.41 (0.67)*	-0.70 (0.16)***	-3.08 (0.24)***
	Both (Mostly Inc)	0.28 (0.05)***	0.11 (0.04)**	-0.91 (0.29)**	-0.18 (0.12)	-1.15 (0.30)***	-0.46 (0.08)***	-0.16 (0.04)***
	New	-0.13 (0.05)**	0.18 (0.04)***	2.45 (0.36)***	-0.28 (0.16)	0.38 (0.28)	0.81 (0.08)***	-2.00 (0.10)***
New	Inc	0.24 (0.19)	0.20 (0.09)*	-1.82 (1.18)	-0.77 (0.64)	-2.17 (1.02)*	-1.85 (0.27)***	-0.78 (0.47)
	Both (Mostly Inc)	0.27 (0.12)*	0.13 (0.07)	-0.44 (0.82)	0.81 (0.36)*	-0.62 (0.62)	-1.41 (0.18)***	1.66 (0.22)***
	Both (Mostly New)	0.02 (0.06)	-0.03 (0.04)	-0.44 (0.46)	0.87 (0.21)***	-0.34 (0.33)	-0.59 (0.09)***	2.12 (0.13)***

Notes: Columns list the coefficient estimates (std. errors in parentheses) for each variable's effect on the probability of transitioning from the "From" to the "To" state relative to remaining in the "From" state (represented as the rows.) Odds ratios can be calculated by exponentiating each coefficient. Coefficient estimates for time indicators are not shown. ***, **, and * indicate significance at the 0.001, 0.01, and 0.05 levels.
[a,b,c]Variables scaled by dividing by 10 (a), 100 (b) , and 100,000 (c).
The table excludes observations in which dealers made fewer than 10 purchases in quarter *t* or quarter *t.*