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Leapfrogging, Cannibalization, and Survival During Disruptive Technological Change: The Critical Role of Rate of Disengagement

Deepa Chandrasekaran, Gerard J. Tellis, and Gareth M. James

Abstract

When faced with new technologies, the incumbents' dilemma is whether to embrace the new technology, stick with their old technology, or invest in both. The entrants' dilemma is whether to target a niche and avoid incumbent reaction or target the mass market and incur the incumbent's wrath. The solution is knowing to what extent the new technology cannibalizes the old one or whether both technologies may exist in tandem. The authors develop a generalized model of the diffusion of successive technologies, which allows for the rate of disengagement from the old technology to differ from the rate of adoption of the new. A low rate of disengagement indicates people hold both technologies (coexistence), whereas a high rate of disengagement indicates they let go of the old technology in favor of the new (cannibalization). The authors test the validity of the model using a simulation of individual-level data. They apply the model to 660 technology pairs and triplet–country combinations from 108 countries spanning 70 years. Data include both penetration and sales plus important case studies. The model helps managers estimate evolving proportions of segments that play different roles in the competition between technologies and predict technological leapfrogging, cannibalization, and coexistence.

Keywords

cannibalization, disengagement, disruption, leapfrogging, new technologies, switching

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In July 2020, Tesla became the world's most valuable automaker, surpassing Toyota in market value for the first time (Roberson 2020). But it was Toyota that in 1997 released the Prius, the world's first mass-produced hybrid electric vehicle. In 2006, Tesla Motors, an upstart entrant, bet that the future of the automotive industry would be fully electric cars. They announced they would produce luxury electric sports cars that could go more than 200 miles on a single charge. Incumbents dismissed the effort as futile because of the high entry barriers for auto production, the high cost of producing in California, and the challenges of establishing charging stations. But Martin Eberhard, Tesla's cofounder, noted in a blog in 2006, "a world of 100% hybrids is still 100% addicted to oil . . . Tesla Motors will remain focused on building the best electric cars for the foreseeable future. With each passing year, our driving range will get longer and the argument for plug-in hybrids will get weaker. To hell with gasoline" (Eberhard 2006).

In contrast, Toyota bet that hybrids would be the future. "The current capabilities of electric vehicles do not meet society's needs, whether it may be the distance the cars can run, or the costs, or how it takes a long time to charge," said Takeshi Uchiyamada, Toyota's vice chairman, who had spearheaded the Prius hybrid in the 1990s (Kubota 2012). Toyota faced a hard choice: invest in hybrids, all-electrics, or both?

Globally, during times of potentially disruptive technological change, both industry incumbents and new entrants face difficult choices. For incumbents, the critical dilemma is whether to cannibalize their own successful offerings and introduce the new (successive) technology, survive with their old offerings, or invest in both. To address this dilemma, they need to know whether disruption is inevitable; that is, will the old technology

Deepa Chandrasekaran is Associate Professor, University of Texas at San Antonio, USA (email: deepa.chandrasekaran@utsa.edu). Gerard J. Tellis is Neely Chaired Professor of American Enterprise, Director of the Center of Global Innovation, and Director of the Institute of Outlier Research in Business, University of Southern California, USA (email: tellis@marshall.usc.edu). Gareth M. James is Deputy Dean, E. Morgan Stanley Chair in Business Administration, and Professor of Data Sciences and Operations, University of Southern California, USA (email: gareth@marshall.usc.edu).

sales decline due to the growth of the new technology and, if so, how much of their existing sales will be cannibalized over time? Or can both old and new technologies, in fact, coexist in tandem? The entrant's dilemma is whether to target a niche and avoid incumbent reaction or target the mass market and incur the wrath of the incumbent (Tellis 2013). To address these dilemmas, both incumbents and new entrants need to know how segments of consumers respond to the successive technology. Examples of technological change abound: electric cars versus hybrid cars versus gasoline cars, OLED TVs versus LCD TVs, streaming versus cable, music downloads versus CDs, laptops versus tablets, and app-enabled ridesharing versus taxicabs. Several incumbent firms have also stumbled or failed during disruptive change: Toyota, GM, HP, Nikon, Canon, Kodak, Sony, Nokia, Yellow Cabs, Comcast, and Sears.

Our central thesis in this article is that to effectively manage disruption, we must answer the following substantive research questions: First, when does an old technology coexist with a new, successive technology versus going into an immediate decline? If coexistence occurs, how can one account for the coexistence of two technologies in an empirical model? Second, how can one estimate the extent of cannibalization and leapfrogging of an old technology by a new technology over time? Third, can consumer segments explain coexistence, cannibalization, and leapfrogging in successive technologies, and if so, which segments?

These questions represent pressing concerns for senior managers (Lehmann, McAlister, and Staelin 2011). To address these questions, we first outline the theory of disruption, discuss research gaps, and define important constructs that are central to the new model and typology. Then, we develop a generalized model of the diffusion of successive technologies. A key feature of the generalized model is the rate of disengagement from the old technology, which is not forced to equal the rate of adoption of the successive technology, allowing both technologies to coexist. Next, we estimate four latent adopter segments from aggregate data, which correlate with the growth of the new technology, the cannibalization of the old, and/or the coexistence of both: leapfroggers, switchers, opportunists, and dual users (defined shortly).

We apply our model to three different types of aggregate data to ascertain model fit: (1) penetration of seven successive technology pairs across 105 countries (441 technology pair–country combinations) spanning multiple years, (2) sales of three contemporaneous technology pairs across 40 countries (92 technology pair–country combinations), and (3) case analyses of real disruption of large incumbents in the United States. The major benefit of using aggregate penetration and/or sales data is that such data are available abundantly compared to individual-level data. Indeed, much research uses this type of aggregate data to generate rich insights on adoption, diffusion, and generational competition (see Chandrasekaran and Tellis 2007; 2008; Koh, Hann, and Raghunathan 2019; Stremersch, Muller, and Peres 2010). In addition, we present a test validating the model using a simulation analysis on individual consumer-level data.

Our model and analysis provide both substantive and modeling innovations. Our research provides a better strategic understanding of how, in many situations, old technologies may not necessarily die but survive when new, successive technologies are introduced. The major contributions and implications are the following: First, disruption, though frequent, is not inevitable even when the successive technology grows rapidly, as old technologies can coexist as partial substitutes of the new. Second, the generalized model of diffusion of successive technologies helps strategists and marketers account for this coexistence by allowing the rate of disengagement from the old technology to differ from the rate of adoption of the new. Third, the separately estimated rate of disengagement enables a superior fit to data on technological succession. Fourth, the model helps estimate cannibalization by new, successive technologies, as well as sizes of four critical segments, providing key signals about disruption. The coexistence of both technologies occurs when there is a large segment of dual users. In contrast, the size of the leapfroggers segment correlates with the growth of the new technology, and the size of switchers and opportunists correlates with cannibalization of the old technology. Fifth, the profit implications of leapfrogging and cannibalization may vary greatly depending on which firms market which technology. Major incumbents may fail during the takeoff of new technologies due to underestimating the size of leapfroggers (opportunity cost) and switchers (real cost). Sixth, the generalized model can capture variations in segment sizes across technologies and global markets. The next sections present the theory, new typology, model, empirical applications, and strategic implications.

Theory

The theory of disruptive change (Bower and Christensen 1995; Christensen 2013) suggests that a new technology enters a market, improves in performance, and then surpasses the performance of the existing technology. During times of such technological change, leading incumbent firms fail, not because they were technologically incapable of producing and marketing these innovations themselves, but because they focus on their existing (mainstream) customers, who were satisfied with the existing technology because it met their needs on the primary dimension of performance (Christensen 2013).

Christensen and his coauthors suggest that the new technology enters, survives, and grows because it offers benefits on a secondary dimension of performance that appeals to niche segment consumers. Over time, the new technology improves in performance and at some point meets the standards of the mainstream segment on the primary dimension of performance. These customers then switch to the new technology. Disruption occurs if the incumbent focuses on the old technology to the exclusion of the new one.

Several authors have criticized the theory of disruption because of circular definitions, lack of large empirical evidence or a predictive model, and a failure to examine whether consumer behavior changes (e.g., Muller 2020; Sood and Tellis

Table 1. A Comparison with Related Literature on Generational Substitution.

Article	Key Question	Data	Partial Disengagement?	Leapfrogging Considered?
This article	To examine the diffusion of successive technologies while accounting for coexistence, cannibalization, and leapfrogging.	Multicountry penetration and sales data across several countries for technology pairs and triplets; case studies; simulation	Yes	Yes (four adopter segments considered)
Koh et al. (2019)	To quantify generational substitution, unbundling, and piracy effects.	Downloadable music; CDs; streaming	No	No
Guo and Chen (2018)	How consumers strategic behavior affects sales and profits for multigeneration products.	Numerical optimization	No	Yes
Shi et al. (2014)	To incorporate consumers' forward-looking behavior in multigenerational models.	Eight products across four firms	No	Yes
Lam and Shankar (2014)	What drives mobile device brand loyalty?	Survey data on attitudes toward mobile phone brands spanning two generations: 2.5 G versus 3G	No	No
Jiang and Jain (2012)	To develop an extension of the Norton–Bass model to separate adopters who substitute an old product generation with a new generation into those who adopted the earlier generation and those who did not.	Two generations of one category in one country; Three generations of one category in one country	No	Yes
Stremersch et al. (2010)	To test whether growth acceleration occurs across multiple product generations.	39 technology generations in 12 product markets	No	Assumes no leapfrogging
Goldenberg and Oreg (2007)	To redefine the laggards concept and link it to the leapfrogging effect.	54 products (not specifically successive generations)	N/A	Yes
Danaher et al. (2001)	To incorporate marketing mix variables in the diffusion of multigeneration products.	Two generations of one category in one country	No	Yes
Kim et al. (2000)	To develop a model able to incorporate both interproduct category and technological substitution effects simultaneously.	One technology market in two countries	No	No
Jun and Park (1999)	To propose a model that incorporates diffusion and choice effects to capture diffusion and substitution for multiple generations of products.	Successive generations of two technology categories, not multicountry	No	Not specifically
Mahajan and Muller (1996)	To develop a model that accounts for diffusion and substitution for successive generations of technological innovations.	Successive generations of one technology category	No	Yes
Norton and Bass (1987)	To develop a model that accounts for both diffusion and substitution for successive generations of high-tech products.	Successive generations of one technology category	No	N/A

2005; 2011; Sood et al. 2012). However, no study has refuted the essential features of the theory of disruption: that successive technologies do compete, the competing technologies appeal to different segments, the new technology grows in performance over time, and the niche it serves grows in response to this improvement.

A major limitation of prior work on disruption is that it does not provide recommendations on some critical issues that concern both incumbents and new entrants: How can they estimate the extent of cannibalization over time and who are the customers most susceptible to the new technology? Could the two technologies coexist, and which segments drive the coexistence of both technologies and the growth of the new technology? This research seeks to address these issues.

Definitions and a Typology of New Adopter Segments for Successive Technologies

To answer the previous questions using the theory of disruption, we define the concepts of successive technology, substitution, and segments.

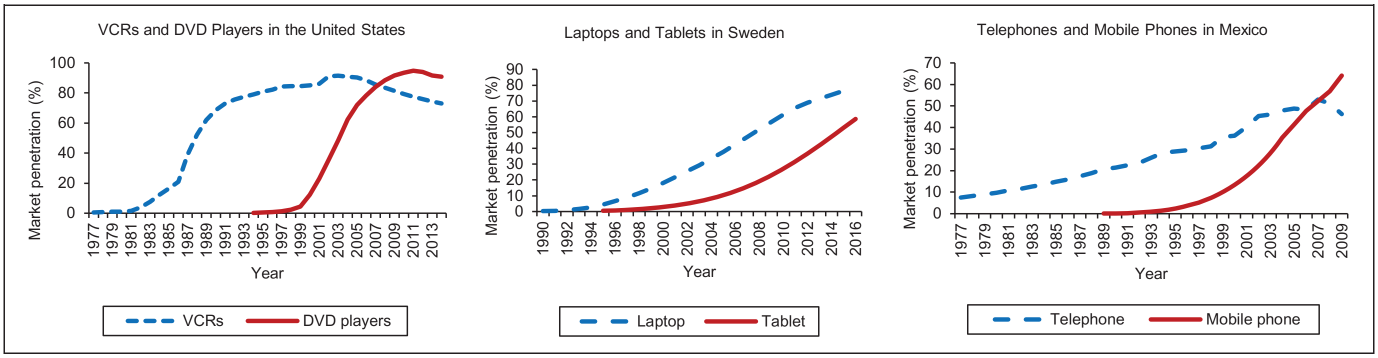

Figure 1a. Market penetration of select technology pairs.

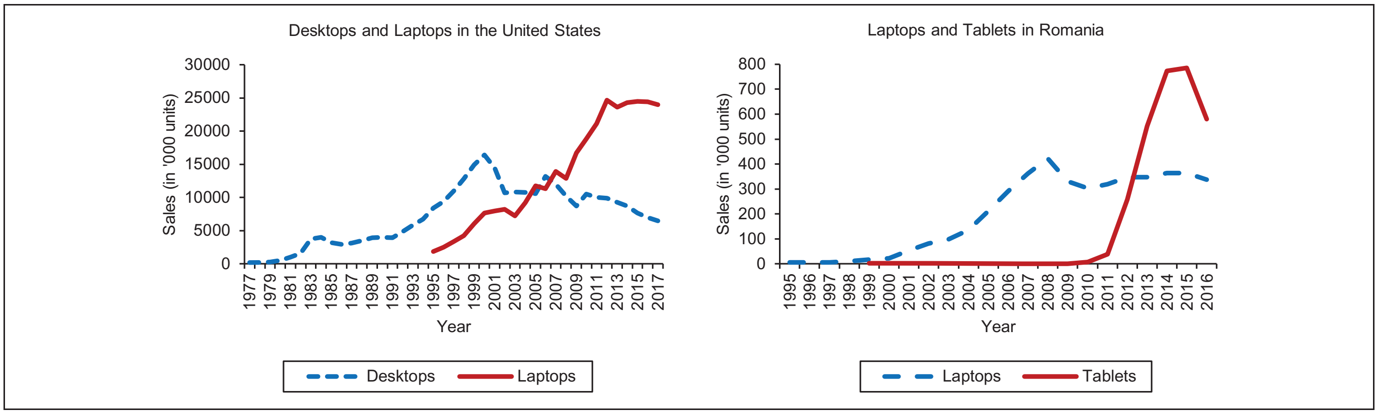

Figure 1b. Sales of select technology pairs.

Successive technology. A new successive technology (which can include both a technology and a product) addresses similar underlying consumer needs as the old technology (e.g., DVR vs. VCR) or may tap simultaneously into multiple needs (e.g., PC, laptop, tablet). Successive technologies do not include new generations of the same product. Note that in this article, we use the term "successive technology" synonymously with "new technology" and the term "old technology" synonymously with "prior technology," given the context of technological succession. "Cannibalization" is the extent to which the successive technology "eats" into real or potential sales (or penetration) of the old technology due to substitution.

Rate of disengagement (F_{12}). Much research in marketing (e.g., Danaher, Hardie, and Putsis 2001; Guo and Chen 2018; Mahajan and Muller 1996; Norton and Bass 1987; Table 1) addresses the related issue of the diffusion of perfectly substitutable successive generations of the same technology (e.g., iPhone 8 vs. iPhone 7), in which the consumer always prefers the new generation to the old at the same price (e.g., iPhone 9 and 10). Thus, successive generations of the same technology exhibit perfect substitution. Here, consumers completely disengage from the old generation (of the same product) when they adopt the new one.

Technological competition is more complex than intergenerational competition because successive technologies may be only partial substitutes. That is, whereas some consumers prefer the successive technology over the old technology (e.g., teens), other consumers may find value in and prefer to hold both (e.g., homeowners who have PCs, laptops, and tablets or keep both mobile phones and landlines). For example, while the two technologies may differ in terms of the scientific principle, the old technology may still serve a need that the successive technology cannot fulfill. In such a case, a group of adopters could choose to hold both technologies, triggering the need for a model that does not force complete substitution. In this case, consumers do not fully disengage from the old technology and may co-own successive technologies.

For example, consider Figure 1a, which plots the penetration of VCRs and the successive technology of DVD players. Here we observe a fast adoption of DVD players, but over this same period, the decline in VCRs (Technology 1) is relatively small. In other words, a number of customers initially held on to both technologies before switching entirely to DVD players. Figure 1a also shows other such examples of the coexistence of successive technologies. Figure 1b shows a similar initial coexistence in sales of technology pairs. Therefore, to model the diffusion of successive technologies, one needs to allow for a rate of disengagement from the preceding technology that is not exactly equal to the rate of adoption of the new technology (i.e., one must allow for partial substitution). This inclusion of a separate rate of disengagement (F_{12} in this article) is one of the innovations we propose in this research. A low rate of disengagement indicates consumers hold on to both technologies, whereas a high rate indicates they discard the old technology in favor of the new. Thus, the greater the rate of disengagement, the greater the cannibalization of the old technology by the new technology.[1]

Adopter segments for a new successive technology. We define and derive mathematically a typology of four adopter segments for successive technologies: (1) "Leapfroggers" adopt the successive technology but would never have adopted the old technology and thus present a new consumer segment for the new technology. This is the niche in Christensen's theory of disruption that provides initial sales for the new technology. (2) "Switchers" are consumers who had already adopted the older technology but who choose to replace it with the successive technology after the latter technology is introduced. In Christensen's theory of disruption, this is the mainstream consumer segment that switches to the successive technology after it improves. The refinement in our empirics is that this segment switches continuously to the successive technology as it improves. Each year, customers switch as the successive technology matches their needs better than the old technology. (3) "Opportunists" are those who would have adopted the old technology but delayed the decision and instead end up adopting the successive technology. (4) "Dual users" are those who had already adopted the older technology but who elect to adopt/use both technologies once the successive technology is introduced. This segment also includes those who would have adopted the old technology but had delayed the decision and ended up adopting and using both technologies.

A Generalized Model of the Diffusion of Successive Technologies

Many situations exist in which one technology substitutes for another but the substitution is only partial, either due to incomplete compatibility or because the old technology still has its uses. Thus, it makes sense to hang on to the old technology because it is still useful (e.g., VHS vs. DVD), even in the presence of the new. Currently, no model allows for this coexistence of successive technologies. However, multigenerational models such as Norton and Bass (1987) and Jiang and Jain (2012) model the diffusion of successive generations of the same technology. Although the Norton and Bass (1987) model is not right for multitechnology substitution, a modification of the Norton–Bass model is well-suited for this context.

Our proposed model uses the multigenerational model of Norton and Bass (1987) as a starting point and extends this model to consider the context of the adoption of successive technologies that do not fully cannibalize each other (partial substitution). The major difference in our model is that we include a rate of disengagement from the old technology that does not equal the rate of adoption of the successive technology, which accounts for partial substitution in the case of successive technologies versus complete substitution in the case of successive generations of the same technology.

Herein, we (1) specify our intuition that motivates the derivation of adopter segments for successive technologies, (2) outline our model for the diffusion of two successive technologies (the Web Appendix provides an extension to multiple technologies), (3) discuss our critical departure from the basic model of multigenerational diffusion (i.e., we provide a more flexible model in which we do not force the rate of disengagement from Technology 1 [this term is used in this section to concisely reflect the old technology] to exactly match the rate of adoption of Technology 2 [we use this term for the successive technology]), and (4) illustrate the equations we used to decompose adoption into four adopter segments.

The Model for Diffusion of Two Successive Technologies

We specify the proposed model for the simplest case of the diffusion over time of two successive technologies as follows. Let $S_1(t)$ and $S_2(t)$ respectively represent the penetration of Technologies 1 and 2 at each time period t. Then we model $S_1(t)$ and $S_2(t)$ as follows:

$$S_1(t) = m_1 F_1(t)\Big(1 - F_{12}(t - \tau_2 + 1)\Big) \quad (1)$$

$$S_2(t) = F_2(t - \tau_2 + 1)\Big(m_2 + m_1 F_1(t)\Big) \quad (2)$$

Note we have added the 1 in Equations 1 and 2 to account for the fact that we are only considering whole years. τ_2 corresponds to the introduction year for Technology 2, and

$$F_g(t) = \frac{p_g\Big(1 - e^{-(p_g + q_g)t}\Big)}{p_g + q_g e^{-(p_g + q_g)t}}, \; t \geq 0, \; g = 1, 2, \text{ or } 12 \quad (3)$$

refers to the fraction of all potential Technology$_g$ consumers for each technology at time t. Here, g refers to a technology (rather than a generation of a technology as is typically considered in the literature on multigenerational diffusion). Our model contains eight parameters: m_1, m_2, p_1, p_2, p_{12}, q_1, q_2, and q_{12}. The parameter m_1 represents the long-run penetration for Technology 1 if Technology 2 had never been introduced. Put another way, prior to the introduction of Technology 2, the penetration for Technology 1 will converge toward m_1 but will never reach m_1 because for $t \geq \tau_2$, Technology 2 will start to reduce the market share of Technology 1. Thus, Technology 2 begins to take market share from Technology 1 upon its introduction. Similarly, m_2 represents the additional market share for Technology 2 above that of Technology 1, so our

[1] Disengagement relates to technological substitution and can be distinguished from churn, which refers to brand switching (e.g., Libai, Muller, and Peres 2009), and from disadoption, wherein the consumer leaves the category entirely for various product and nonproduct reasons (Lehmann and Parker 2017).

model assumes that the long-run penetration for Technology 2 will equal $m_1 + m_2$. The parameters p_1 and p_2 are the coefficients of innovation for Technologies 1 and 2, respectively, and q_1 and q_2 are the coefficients of imitation for Technologies 1 and 2, respectively. p_{12} and q_{12} can then be thought of as the coefficients of disengagement. Thus, F_1 describes the rate at which customers adopt Technology 1 prior to the introduction of Technology 2, and F_2 models the rate of adoption of Technology 2 after its introduction. Finally, F_{12} models the rate at which Technology 1 customers disengage upon the introduction of Technology 2.

Note that we make two critical departures in this specification from what is typical of multigenerational diffusion models. Typically, multigenerational diffusion models restrict F_2 to equal F_{12}. The proposed model removes such a restriction for the context of successive technologies. The potential advantage of modeling F_2 and F_{12} separately is as follows: when $F_2 = F_{12}$, the rate of disengagement by current Technology 1 customers exactly matches the rate of adoption by Technology 2 customers. However, in the case of successive technologies, across categories and countries, consumers may in fact hold both technologies simultaneously. For example, many families with older members have both a landline and a mobile phone. In addition, both technologies may grow simultaneously in different customer segments. Therefore, one of our innovations in developing a corresponding model to fit the context of successive technologies is to allow F_{12} to be less than F_2, which corresponds to people adopting Technology 2 at a faster rate than they leave Technology 1. If $F_{12} = 0$, then there is no substitution effect and people are holding on to both technologies. When F_{12} is large, there is a large substitution effect. This is a strength of the model because we can directly measure the substitution effect rather than forcing F_2 to equal F_{12}.

Second, an important distinction from prior models is that we also do not constrain p_1 to equal p_2 or q_1 to equal q_2, a constraint that is suitable when the changes between the two generations are incremental, as in multigenerational diffusion, but not when the technology is discontinuous (Mahajan and Muller 1996), as in our more general case of successive technologies. Given that each successive new technology provides a substantial improvement in benefits, we expect the diffusion parameters p and q to vary for each new technology in a pair or triplet. Thus, our model does not constrain p_1 to equal p_2 or q_1 to equal q_2.

Note that, similar to previous models, we make certain assumptions. First, we assume a pure Bass model formulation for the first technology (Bass 1969). However, we acknowledge that the first technology may have been affected by a previous technology. Second, we model F_{12} using the same functional form as F_1 and F_2 for two reasons. Empirically, we find that the model with this form fits our data well. In addition, by modeling F_{12} using the same functional form as F_2, our approach reduces to the standard Norton and Bass (1987) and Jiang and Jain (2012) formulations whenever $F_{12} = F_2$. Thus, we provide a strict generalization of previous models. Overall, however, our model is a generalized model that can apply to both generational diffusion and technology diffusion.

Model Estimation

Let S_{ig} represent the observed yearly penetration of Technology g at time t_i. Then, estimating the eight parameters in Equations 1, 2, and 3 can be achieved using nonlinear least squares. In particular, we select m_1, m_2, p_1, p_2, p_{12}, q_1, q_2, and q_{12} as the values that minimize

$$\sum_{i=1}^{n}\Big(S_{i1} - m_1F_1(t_i)\Big(1 - F_{12}(t_i - \tau_2 + 1)\Big)\Big)^2 + \sum_{i=1}^{n}\Big(S_{i2} - F_2(t_i - \tau_2 + 1)\Big(m_2 + m_1F_1(t_i)\Big)\Big)^2, \tag{4}$$

where n represents the number of years of observation. We minimize Equation 4 using the NLS function in the statistical software package R. Once the parameters have been estimated, it is a simple matter to plug the estimates back into Equations 1 and 2 to predict future penetration for Technologies 1 and 2.

Computing Segments of Adopters for the New Successive Technology

Next, we decompose penetration of Technology 2 into the four major segments defined earlier. Switchers (SW) and opportunists (O) represent a lost market for Technology 1 and thus its cannibalization (CAN), whereas leapfroggers (L) and dual users (DU) represent market growth (MG). Therefore, $S_2(t)$ comprises the sum of these segments as such:

$$\begin{aligned} S_2(t) &= MG_2(t) + CAN_2(t) \\ &= \underbrace{L_2(t) + DU_2(t)}_{\text{Market growth}} + \underbrace{SW_2(t) + O_2(t)}_{\text{Cannibalization}}. \end{aligned} \tag{5}$$

Similarly, $S_1(t)$ comprises the initial market for this technology (L_1) less cannibalization from Technology 2 as such:

$$S_1(t) = L_1(t) - CAN_2(t) = L_1(t) - \underbrace{(SW_2(t) + O_2(t))}_{\text{Cannibalization}}. \tag{6}$$

We derive the various consumer segments as follows:

$$L_1(t) = m_1F_1(t),\ L_2(t) = m_2F_2(t - \tau_2 + 1) \tag{7}$$

$$SW_2(t) = m_1\sum_{\theta=\tau_2}^{t}F_1(\theta - 1)\Big(F_{12}(\theta - \tau_2 + 1) - F_{12}(\theta - \tau_2)\Big) \tag{8}$$

$$O_2(t) = m_1 \sum_{\theta=\tau_2}^{t} F_{12}(\theta - \tau_2 + 1) \Big(F_1(\theta) - F_1(\theta - 1)\Big) \tag{9}$$

$$DU_2(t) = m_1 F_1(t)\tilde{F}_2(t - \tau_2 + 1), \tag{10}$$

where $\tilde{F}_2(t) = F_2(t) - F_{12}(t)$.

It is not hard to verify that the four quantities in Equations 7–10 satisfy Equations 5 and 6. Let us first consider $L_2(t)$. Recall that m_2 represents the total potential additional market for Technology 2 beyond that of Technology 1 and F_2 provides the fraction of potential customers who have actually adopted the new technology. Thus, $L_2(t)$ corresponds to the total number of additional Technology 2 adopters who would never have adopted Technology 1. Next, consider $O_2(t)$. Note that $m_1(F_1(\theta) - F_1(\theta - 1))$ represents the number of customers who would be expected to adopt Technology 1 in time period θ. However, F_{12} of these customers switch directly to Technology 2, while $\tilde{F}_2 = F_2 - F_{12}$ customers adopt both technologies. Therefore, summing from τ_2 up to t gives the total number of opportunists (Equation 9). $DU_2(t)$ corresponds to dual users who adopt both technologies. Here, $m_1 F_1(t)$ represents the number of people who have adopted Technology 1, and $\tilde{F}_2(t)$ represents the fraction of these people who have adopted both technologies.

Finally, the switchers correspond to the remaining adopters of Technology 2, which can be shown to correspond to Equation 8. At $\theta = \tau_2$, this equation is fairly intuitive because $m_1 F_1(\tau_2 - 1)$ represents the current number of Technology 1 adopters and $F_{12}(t)$ represents the fraction of potential customers who drop Technology 1 to adopt Technology 2 in period $\theta = \tau_2$. Thus, Equation 8 assumes that current customers of Technology 1 switch to Technology 2 at the same rate as noncustomers of Technology 1. However, for $\theta > \tau_2$, the intuition becomes more complicated because the number of Technology 1 customers will be less than $m_1 F_1(t - 1)$ as a result of prior switching.

Note that we have chosen to focus on identifying the adopters of the new technology. While we consider the role of dual users, who continue to find value in the old technology, we do not distinguish, for the sake of simplicity, between other types of old technology adopters—for example, those who may never adopt either technology, those who are yet to adopt the old technology but will not adopt the newer technology, and those who will stay loyal to the old technology.

We can extend this model to more than two technologies. In markets characterized by excessive turbulence, a third technology is often introduced in quick succession to the second technology. We can extend our model to account for $G \geq 2$ different technologies: $S_1(t), S_2(t), \ldots, S_G(t)$. Here, successive technologies cannibalize the market of earlier technologies. In the interest of brevity, we detail the model extension to three technologies and its application for data on technology triplets in Web Appendix W1.

Model Benefits

The proposed model allows us to extract the sizes of the four adopter segments for each year and technology pair in each country using the defined equations. Our model has several additional desirable characteristics. First, the model parameters have natural interpretations. For example, F_g corresponds to the rate that individuals would adopt technology g in the absence of any competing technologies, and $F_{g-1,g}$ represents the rate that individuals disengage from Technology $g - 1$ to adopt Technology g. Second, by setting $F_{g-1,g} = F_g$, our model reduces to that of Norton and Bass (1987) and Jiang and Jain (2012), so their model can be seen as a special but more restrictive version of our approach for this context. Our empirical results suggest that our model provides a significantly more accurate fit to the data on successive technologies. Third, market growth generated by a particular technology can be easily computed as the sum of leapfroggers and dual users, and cannibalization can be computed as the sum of switchers and opportunists. Fourth, we do not place any restrictions on the size of adopter segments. Thus, market growth can be positive or negative. The latter case occurs when the total market size actually declines with the introduction of a new technology, possibly indicating disruption by yet another technology. While not the norm, our empirical results suggest that market growth can at times be negative when a still newer technology emerges for which we do not have data.

Model Validation: Can the Model Recover Meaningful Structure from Individual Data?

One may ask what evidence we have that our model can correctly recover individual consumer segments given that we have only aggregate data. To validate our model for this purpose, we ran a series of simulation analyses following precedents in model simulation (Paulson, Luo, and James 2018; Tellis and Franses 2006). For our data generation process, we simulated the adoption of two technologies by a large group of individual customers. The simulation demonstrates a good fit with only ten years of data for Technology 1 (i.e., the model yields a reasonably good fit with only five years after Technology 2 enters the market) (Simulation Exercise 1). With more years of simulated data, the fits become even more accurate. Next, we show the robustness of the simulation analysis to the inclusion of a continuous heterogeneity distribution (Simulation Exercise 2) and the absence of some of the segments altogether (Simulation Exercise 3). These exercises provide more confidence that our model can uncover meaningful structure from the aggregate data even when the model assumptions do not hold exactly. Details are in Web Appendix W2.

Empirical Applications of the Model

This section covers applications of the model using data from different contexts.

Table 2. In- and Out-of-Sample Fit Statistics for Technology Pairs Using Penetration Data.

Training Errors on Model where $F_2 = F_{12}$							
Tech 1	**Tech 2**	**Tech 1 Mean**	**Tech 2 Mean**	**Overall Mean**	**Tech 1 Median**	**Tech 2 Median**	**Overall Median**
Laptop	Tablet	.0043	.0009	.0026	.0006	.0001	.0003
Personal computer	Laptop	.0123	.0016	.0070	.0018	.0003	.0010
DVD player	Blu-ray	.0015	.0001	.0008	.0004	.0000	.0002
VCR	DVD player	.0032	.0082	.0057	.0012	.0056	.0018
Test Errors on Model where $F_2 = F_{12}$							
Tech 1	**Tech 2**	**Tech 1 Mean**	**Tech 2 Mean**	**Overall Mean**	**Tech 1 Median**	**Tech 2 Median**	**Overall Median**
Laptop	Tablet	.0324	.0134	.0229	.0030	.0012	.0023
Personal computer	Laptop	.0390	.0131	.0260	.0031	.0017	.0025
DVD player	Blu-ray	.0491	.0073	.0282	.0013	.0034	.0020
VCR	DVD player	.0096	.1223	.0659	.0025	.0567	.0089
Training Errors on Our Method with $\mathbf{F_2 \neq F_{12}}$							
Tech 1	**Tech 2**	**Tech 1 Mean**	**Tech 2 Mean**	**Overall Mean**	**Tech 1 Median**	**Tech 2 Median**	**Overall Median**
Laptop	Tablet	.0014	.0002	.0008	.0003	.0000	.0001
Personal computer	Laptop	.0024	.0004	.0014	.0013	.0000	.0005
DVD player	Blu-ray	.0011	.0000	.0006	.0004	.0000	.0001
VCR	DVD player	.0008	.0014	.0011	.0004	.0005	.0005
Test Errors on Our Method with $\mathbf{F_2 \neq F_{12}}$							
Tech 1	**Tech 2**	**Tech 1 Mean**	**Tech 2 Mean**	**Overall Mean**	**Tech 1 Median**	**Tech 2 Median**	**Overall Median**
Laptop	Tablet	.0072	.0017	.0045	.0012	.0001	.0003
Personal computer	Laptop	.0084	.0035	.0059	.0012	.0003	.0007
DVD player	Blu-ray	.0530	.0033	.0281	.0023	.0009	.0014
VCR	DVD player	.0027	.0622	.0325	.0006	.0053	.0015

Analysis of Cross-Country Penetration of Technology Pairs

We examined the fit of the model using the market penetration[2] of seven technology pairs (telephone–mobile phone, dial-up internet–broadband, black-and-white TV–color TV, VCR–DVD player/recorder, DVD player–Blu-ray player, personal computer–laptop, and laptop–tablet) spanning 105 countries (441 technology pair–country combinations). The data were compiled from several sources (Passport Euromonitor, Fast Facts Database, and the telecommunications database of the International Telecommunications Union).

Model fit. Overall, the proposed model fits the data well. Table 2 presents comparisons of the penetration data for four technology pairs using both mean-squared and median-squared errors of our proposed model with the separately estimated disengagement rate compared to the reduced form model using the simplifying assumption $F_2 = F_{12}$. Our proposed model gets much smaller error rates than the latter model.

Table 2 presents the results by old and new technology as well as the average error across both technologies for the four pairs (the subsample is displayed for brevity). We derived the mean errors in the "training," or in-sample data, by excluding the last time point for each curve, fitting each of the two competing models to the remaining time points, and calculating the mean of squared errors between the observed and predicted points for each technology pair across countries. In contrast, we derived the "test," or out-of-sample results, by excluding the last time point from each curve and fitting the models to the remaining time points ($K = 1$). However, in this case, the mean squared error is calculated using the squared difference between the final year's observed and predicted points and calculating the overall average error across countries for each technology pair. Overall, our model fits much better out of sample as well as in sample, which is the true test for better performance of our model. The median error rate refers to the in-sample and out-of-sample error rate across the different countries—using the median instead of the mean—to account for the fact that some countries may greatly influence the

[2] The measurement unit is market penetration or the percentage of households owning a technology. Penetration refers to the number of adopters divided by the number of households or inhabitants (depending on the data available for each technology pair).

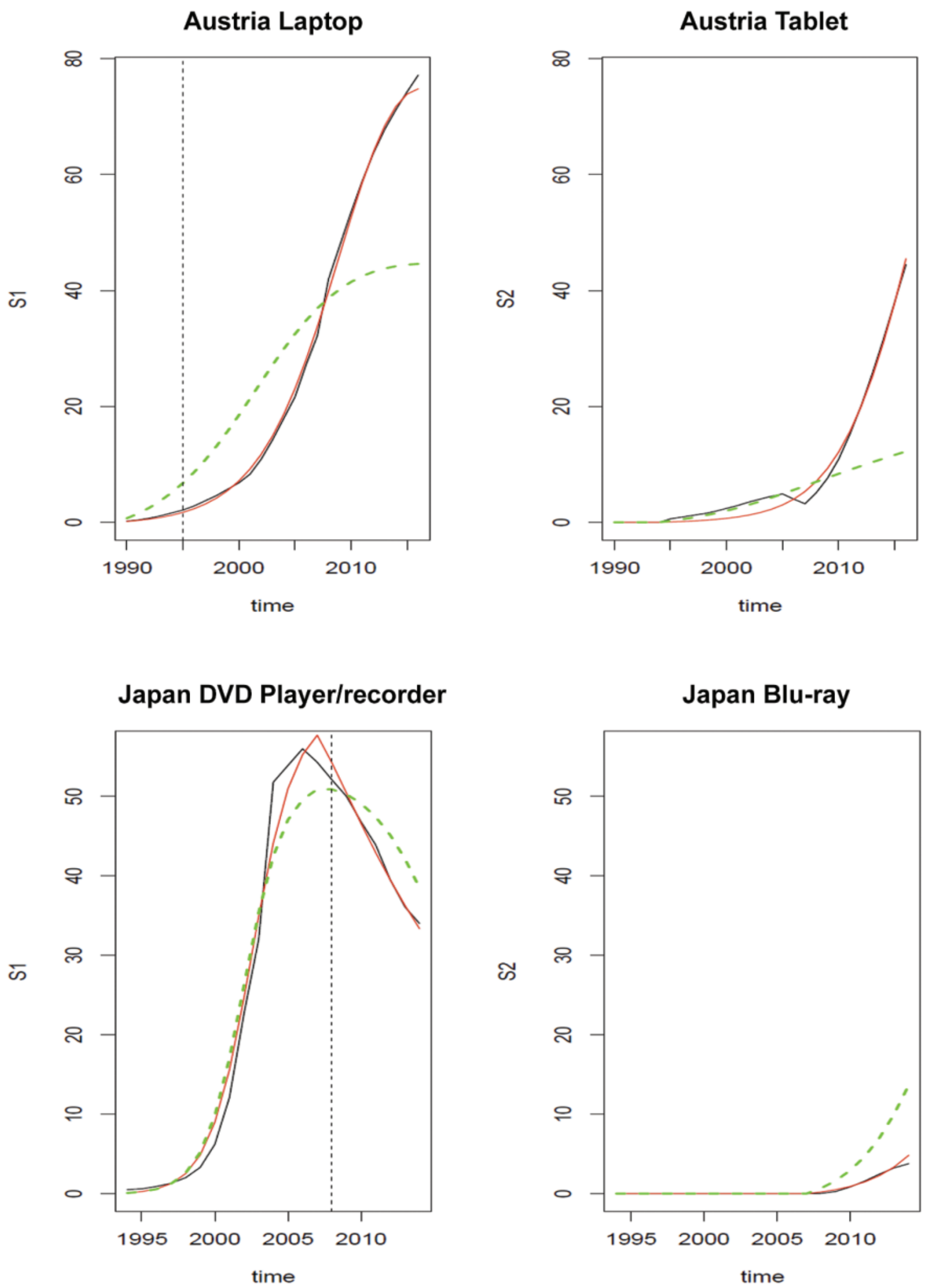

Figure 2. Sample fit plots from application of model with penetration data.

Notes: Displayed are the fit plots for sample technology pairs. The black lines are the real data. The red line is plotted using our model ($F_2 \neq F_{12}$) and the green dashed line is for the model with $F_2 = F_{12}$. The vertical lines represent the year of introduction of the new technology into the market.

averages.[3] See Figure 2 for some illustrative fit plots. Web Appendix W3 presents an analysis for K = 3 and 5 years. Overall, this analysis indicates that our model, which allows $F_{12} < F_2$, still outperforms a model that allows $F_{12} = F_2$. Table 3 provides the mean parameter estimates for these technology pairs.

Our model allows us to decompose penetration for technology pairs into adopter segments. We provide an illustrative example for telephone–mobile phones in India. In Figure 3a, L1 is the projected penetration of Technology 1 (telephone) if the successive technology (mobile phone) were absent. S1 is

[3] All the raw numbers for this analysis were standardized using the largest observed penetration level within each country to provide for a valid comparison across countries.

Table 3. Parameter Definitions and Estimates.

Parameter	Interpretation	Laptop–Tablet		PC–Laptop		DVD–Blu-ray Player		VCR–DVD Player	
		M	SD	M	SD	M	SD	M	SD
m1	Long-run penetration potential for Technology 1 if Technology 2 had never been introduced	76.65	54.49	81.69	30.62	73.08	41.35	66.65	35.63
m2	Additional market share for Technology 2 above that of Technology 1	20.60	24.83	11.06	17.61	16.93	46.81	9.15	15.16
p1	Coefficient of innovation for Technology 1	.004	.010	.002	.004	.005	.014	.039	.048
q1	Coefficient of imitation for Technology 1	.250	.056	.221	.061	.544	.164	.182	.130
p2	Coefficient of innovation for Technology 2	.006	.011	.007	.008	.012	.015	.007	.010
q2	Coefficient of imitation for Technology 2	.222	.109	.172	.071	.162	.140	.521	.262
p12	Coefficient of disengagement 1	.003	.013	.001	.002	.014	.025	.011	.021
q12	Coefficient of disengagement 2	.022	.056	.025	.049	.157	.295	.193	.118
N	Count	85		85		41		41	

the estimated penetration for Technology 1, indicating the effect of cannibalization (L1 − Cannibalization) due to switchers (SW) and opportunists (O). In Figure 3b, S2 (penetration for Technology 2 (mobile phone) is decomposed into leapfroggers (L2), total cannibalization (switchers (SW) + opportunists (O)), and dual users (DU). Here, the penetration of mobile phones is initially dominated by leapfroggers, followed by growth from cannibalization. In Figure 3c, S1 + S2 represents the evolution of the overall market due to market growth from Technology 2 (leapfroggers + dual users) compared to the presence of only Technology 1 (L1). Overall, the introduction of mobile phones in India created market expansion.

Are Adopters of Successive Technologies Similar Across Categories?

We next present some key results derived from decomposition of the data across the 441 technology pair–country combinations ten years from the commercialization of the new technology, using our model. Figure 4a presents the average size of the adopter segments across categories. Notice that for the transition from dial-up to broadband, on average across countries, switchers form the dominant category in terms of market penetration (8%), followed by leapfroggers (6%), rather than dual users. In terms of validity, these results make sense because most adopters are unlikely to hold both dial-up and broadband. In contrast, for landline telephones–mobile phone, dual users (24%) dominate on average across countries; in other words, most adopters were keen on holding both technologies ten years from the commercialization of the new technology.

Furthermore, on average, growth of Technology 2 derived from cannibalization of Technology 1 due to switchers and opportunists is greater than from market growth due to leapfroggers and dual users for the Blu-ray and broadband markets. In contrast, market growth is greater than cannibalization for the other technology pairs. Overall, the results indicate the size of adopter segments and the effects of leapfrogging and cannibalization vary across categories.

Are Adopter Segments Similar Across Countries?

Following marketing research discussing cross-country effects with multiple data sets (e.g., Ladron-de-Guevara and Putsis 2015; Putsis et al. 1997), we examine if adopter segments vary across countries. We classify countries in our data set into developing and developed countries. Specifically, we use the analytical classification provided by the World Bank and gathered from various historical reports, as income classifications are rigorous and contemporaneous.[4] We term low and low-middle income countries as developing and middle and high-income countries as developed. We present the following results using data from 323 technology pair–country combinations in which we were able to identify the country income classification as of Year 10 from new technology commercialization. We identify 131 cases of high-income countries, 88 of upper-middle income, and 104 of low-income (includes low and low-middle income) countries.

The mean estimated penetration of Technology 2 ten years after the new successive technology commercialization is 18% for low-income countries and 23% for high-income countries. The mean estimated penetration of Technology 1 ten years after new technology commercialization is 24% for low-income countries and 49% for high-income countries. These estimates were very close to the actual penetration data for that year.

Overall, the mean for leapfroggers is significantly higher for low-income countries compared to both high-income countries ($\text{MeanL}_{\text{lowinc}} = 7.04$, $\text{MeanL}_{\text{highinc}} = 2.61$, $t = 4.10$, $p = .0001$, using a two-sample T-test with unequal variances) and upper-middle-income countries ($\text{MeanL}_{\text{uminc}} = 4.21$, $t = 2.09$, $p = .038$). The mean for dual users is significantly higher for high-income compared with low-income countries

[4] Each year, the World Bank revises the analytical classification of the world's economies on the basis of estimates of gross national income per capita for the previous year and classifies countries into low-income, lower-middle-income, upper-middle-income, and high-income countries.

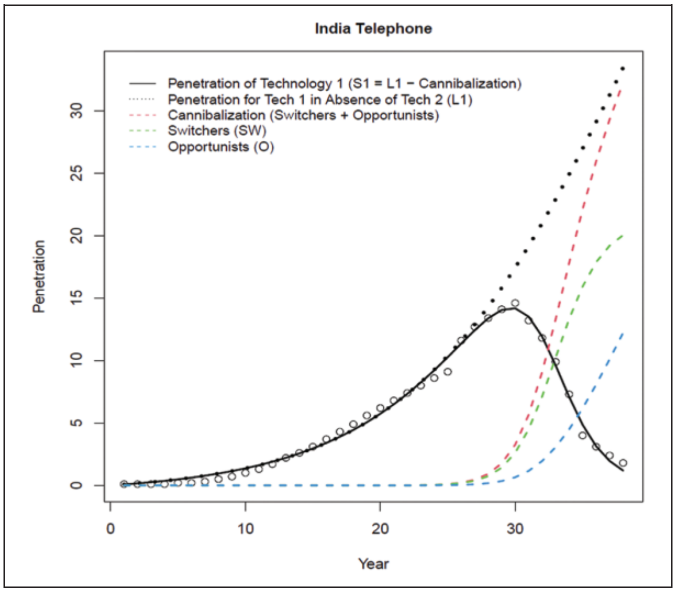

Figure 3a. Decomposition of penetration of telephone (old technology) in India.

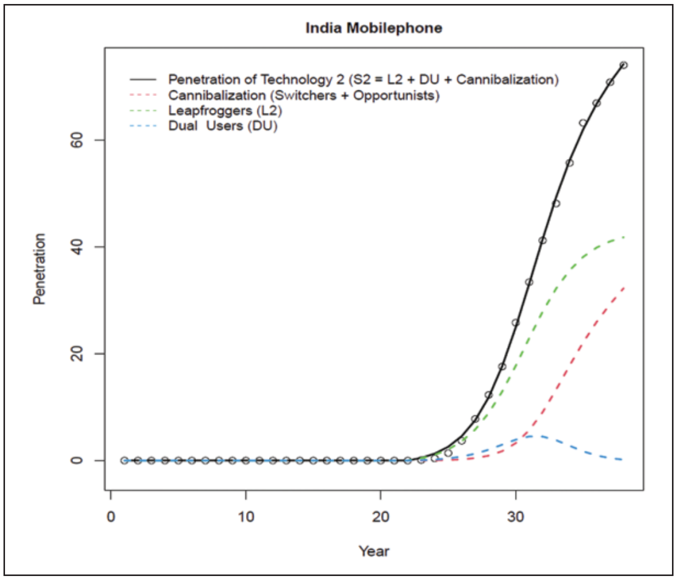

Figure 3b. Decomposition of penetration of mobile phone (new technology) in India.

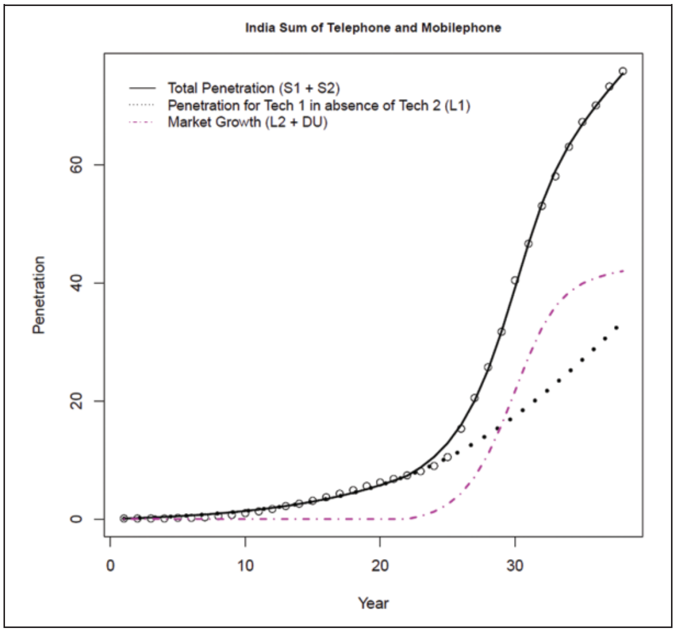

Figure 3c. Evolution of the market (India telephone and mobile phone).

Notes: Figure 3a shows the projected penetration L1 of Technology 1 if the successive technology were absent and the effect after cannibalization from Technology 2, represented by S1, the estimated penetration. Figure 3b shows the breakdown of the penetration curve (S2) for Technology 2 (mobile phone in India) into leapfroggers (L2), cannibalization (switchers [SW] + opportunists [O]), and dual users (DU). Figure 3c shows the evolution of the overall market (S1 + S2) due to market growth (MG) from Technology 2 (leapfroggers + dual users) compared to the market in the presence of only Technology 1 (L1). The figures are plotted over the lifetime of available data for Technology 1.

($MeanDU_{highinc} = 16.29$, $MeanDU_{lowinc} = 6.23$, $t = 4.97$, $p < .0001$) and upper-middle-income countries ($MeanDU_{uminc} = 9.10$, $t = 3.12$, $p = .002$).

Thus, a key empirical generalization from our analysis is that developing countries exhibit a higher level of leapfrogging adoption than developed countries in the early life cycle of the successive technology, whereas developed countries exhibit a higher level of adoption by dual users than developing countries in the early life cycle of the successive technology (Figure 4b).

Overall, we find that adopter segments of successive technologies have some context-dependent variations, validating the need for a generalizable model that managers can use to understand the extent of cannibalization and/or market growth.

Analysis of Data on Cross-Country Sales of Technology Pairs

Next, we examine whether the model fits aggregate sales data. We use historical sales data (units in thousands) on three contemporary technology pairs (laptops–tablets, DVD players–Blu-ray players, and digital cameras–smartphones) from 40 countries, with 92 product–country combinations in total for the years 1990–2017 from the Euromonitor Passport database[5].

Fit statistics. Table 4 shows the fit statistics. Results indicate that our model with a separately estimated disengagement also fits sales data well. The mean parameter estimates across the 92 product–country combinations are $p_1 = .02$ (SD = .09),

[5] To determine early sales data more accurately in each country, we compared the earliest year of sales data with the corresponding penetration data from Euromonitor. Whenever penetration data started earlier, we used a simple proportion formula to calculate sales for earlier years.

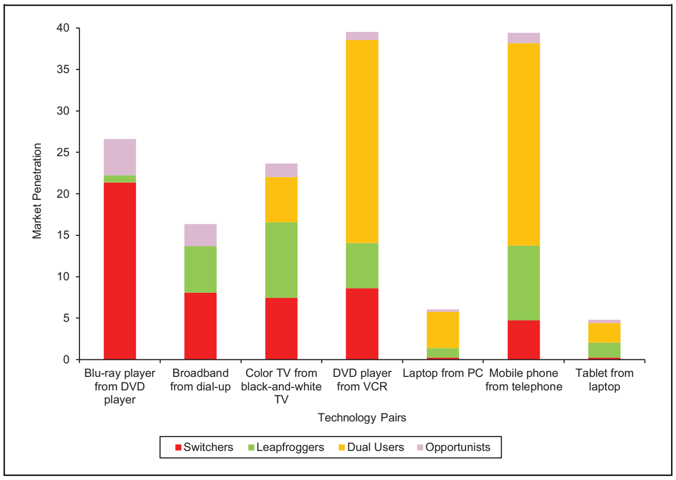

Figure 4a. Decomposition by adopter segments across technology pairs.

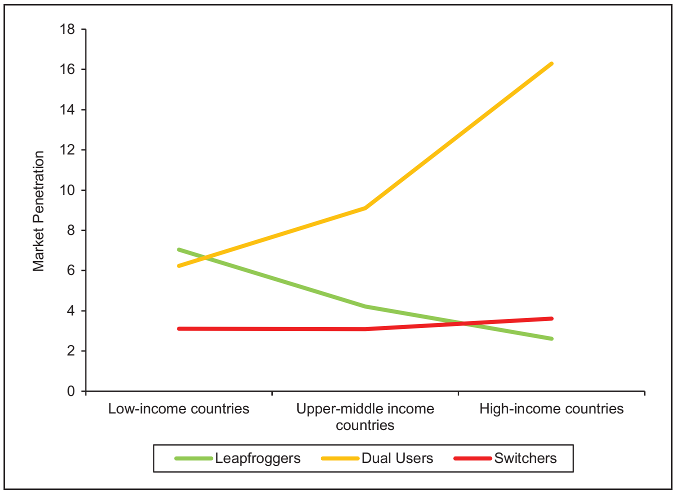

Figure 4b. Decomposition of adopter segments across income classifications of countries.

q_1 =.54 (SD = .34), p_2 =.02 (SD = .03), q_2 =.29 (SD = .32), p_{12} =.09 (SD = .12) and q_{12} =.34 (SD = .33).

Case Analyses of Successive Technology Competitions in the United States

We next apply our model to the competition within contemporary, emerging technology pairs in the United States. The application leads to some preliminary generalizations: First, an increase in switchers over time is associated with the cannibalization of sales of Technology 1. Especially when switchers dominate dual users, this increase in switchers is associated with a sustained decline of sales of Technology 1, disrupting incumbents (Cases 1, 4, Web Appendix W4 Case WA1 on digital camera–smartphones). Second, an increase in dual users over time compared with switchers buys time for older technologies and enables them to grow despite the growth of new technologies (Case 2, Web Appendix W4 Case WA2 on VCRs–DVD players). Third, an increase in and dominance of leapfroggers over time is associated with the growth of Technology 2 (Cases 2, 3, Web Appendix W4 Case WA1). Incumbents underestimate or ignore these entirely new consumer segments. Christensen mentioned this, but we show how to estimate its size and evolution.

Case 1: Music CDs versus digital downloads. CDs were the dominant music format in 2004, and Apple iTunes' music store had been offering legal digital music downloads since 2003. Although most music executives then believed that people would pay for legal online music, big record labels were slow in adopting digital downloads. Some industry analysts predicted that digital music would not replace CDs because either potential buyers would use it only to sample music before buying CDs or it would only be the terrain of teenagers using iPods (Emigh 2008). According to analyst expectations, digital downloads and CDs could be expected to grow in tandem. A pertinent question in 2004 was whether digital downloads would eventually cannibalize and disrupt music CDs or if both would in fact grow in tandem.

We analyzed data on sales (in millions of units) of music CDs (CDs and CD singles from 1983 to 2018) and digital downloads (including singles, music albums, and music videos from 2004 to 2018) from the Recording Industry Association of America. The analysis from our model (Figure 5a) suggests that switchers (red line) dominated other segments right from the beginning, and this segment grew over the years. Both dual users (orange line) and leapfroggers (green line) tapered off by Year 5. Thus, contrary to the analysts' early expectations, our model indicates that the technologies did not coexist. The immediate high cannibalization by switchers was associated with and probably responsible for the relatively rapid decline of music CDs.

The decline of music CDs from 2005 caused both record labels and music retailers to suffer. About 800 music stores closed in 2006 alone (Smith 2007).

Case 2: Tablets versus laptops. While PCs and laptops were the dominant older technologies, the tablet, which was in the works for many years, took off with the introduction of the Apple iPad. At the D8 conference in 2010, when Walt Mossberg asked Steve Jobs whether he thought the tablet will replace the laptop, Jobs replied "PCs are going to be like trucks. They are still going to be around, they are still going to have a lot of value, but they are going to be used by one out of X people- Is the next step the iPad? Who knows? Will it happen next year or five years from now or seven years from now? Who knows? But I think we're headed in that direction" (Paczkowski 2010). HP dominated the market for the older technologies, but in 2011, CEO Leo Apotheker wanted to get HP out of the PC business (Goldman 2011). "The effect is real," Apotheker is reported to have said on the call with analysts, "consumers are changing how they use PCs." Apotheker was soon ousted, and the decision was reversed. A pertinent question at this time was

Table 4. Comparison of Fit Statistics for Sales Data of Technology Pairs.

1. Laptop Versus Tablet Across Countries

Mean Errors	**Laptop**		**Tablet**		**Overall**	
	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$
Training	.0067	.0073	.0114	.0106	.0090	.0090
Test	.0196	.0119	.1491	.0996	.0843	.0557
Median Errors	**Laptop**		**Tablet**		**Overall**	
	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$
Training	.0036	.0036	.0116	.0108	.0068	.0072
Test	.0114	.0046	.1509	.0900	.0354	.0163

2. DVD Versus BD players Across Countries

Mean Errors	**DVD player**		**BD player**		**Overall**	
	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$
Training	.0219	.0045	.0084	.0017	.0152	.0031
Test	.0294	.0028	.1165	.0224	.0730	.0126
Median Errors	**DVD player**		**BD player**		**Overall**	
	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$
Training	.0199	.0034	.0070	.0008	.0115	.0022
Test	.0231	.0006	.1019	.0108	.0505	.0019

3. Digital Cameras Versus Smartphones Across Countries

Mean Errors	**Digital Cameras**		**Smartphones**		**Overall**	
	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$
Training	.0010	.0003	.0063	.0022	.0036	.0013
Test	.0008	.0002	.0214	.0124	.0111	.0063
Median Errors	**Digital Cameras**		**Smartphones**		**Overall**	
	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$	Model with $F_2 = F_{12}$	Our Model with $F_2 \neq F_{12}$
Training	.0008	.0002	.0018	.0009	.0012	.0004
Test	.0001	.0001	.0050	.0028	.0014	.0002

Notes: This table represents the in-sample (training) and out-of-sample (test) error rates for sales data. The explanations are similar to those provided for Table 2. All the raw numbers for this analysis were standardized by the largest observed sales level by each country to provide for a valid comparison by countries. The median error rate refers to the in-sample and out-of-sample error rate across the different countries—using the median instead of the mean—to account for the fact that some countries may greatly influence the averages.

whether tablets would eventually cannibalize and disrupt sales of laptops (and PCs).

We analyzed U.S. sales data of laptops and tablets from Passport Euromonitor. Figure 5b shows that while leapfroggers (green line) were the dominant segment, switchers (red line) dominated dual users (orange line) in the first ten years, vindicating HP's initial bleak assessment. However, soon after, dual users (using both technologies) dominated switchers. Our analysis indicates why tablets would not immediately disrupt the market for laptops. Apple gained by attracting dual users while also capturing an entirely new adopter segment base: leapfroggers.

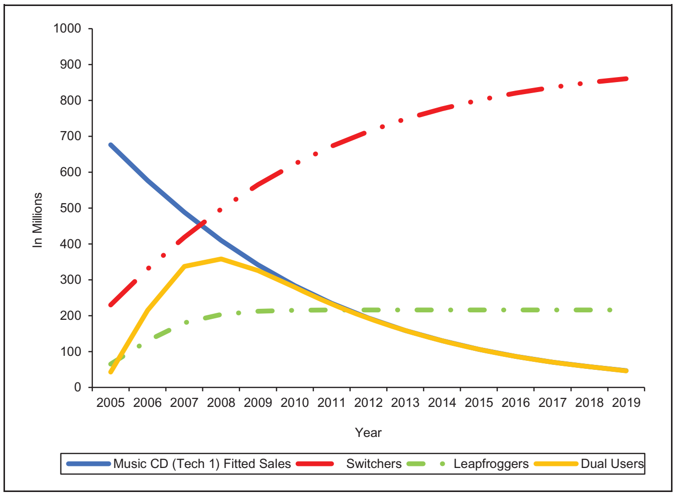

Figure 5a. Decomposition of music CDs and digital downloads in the United States.

Case 3: Hybrids versus all-electric cars. Next, we examine the case of hybrid cars versus all-electric cars.[6] When Tesla first commercialized the electric vehicle, senior managers and analysts scoffed at the idea for three reasons: (1) no domestic firm had successfully introduced a new automobile for a hundred years; (2) automobile manufacturing is asset-intensive, making the break-even point unacceptably high; and (3) California was a state with very high labor costs, especially in comparison to Japan, Korea, and China. To resolve these issues, the critical question for the entrant and the incumbent was whether to invest in hybrid cars, all-electric cars, or both.

To answer this question, we use our model to decompose U.S. retail car sales (in thousands of units) of hybrids (including plug-in hybrids) and all-electric cars, obtained from the Transportation Energy Data Book in the time interval 2000–2018. Results in Figure 5c indicate that the growth of all-electric car sales is driven by a predominance of leapfroggers (green line), while switchers (red line) also grow, albeit slowly. Because all-electric cars represent an emergent technology, we have only eight years of new technology data up to 2018. We use data until 2018 and predict two years ahead. Our model predicts that sales of electric cars would cross sales of hybrids in 2020 (two years ahead), driven predominantly by leapfroggers.

Investors may be anticipating Tesla to dominate this race. Before the COVID-19 crisis overtook global markets, Tesla reached a market valuation of $102 billion in January 2020, trailing only Toyota (Roper 2020). In July 2020, Tesla was worth more than Toyota (Roberson 2020). Investors are putting pressure on leading incumbents in gasoline and hybrids to invest in all-electric (Foldy 2020).

Case 4: Taxis versus ride-sharing services in New York City. We next examine the emergent technology of ride-sharing services such as Uber and Lyft. Because the data for this case were available only for New York City, we limit our analysis to only this city. In many American cities, including New York, drivers need a medallion to operate a taxi, and the city issues a fixed number of them. The ride-sharing service Uber arrived in New York in 2011. Ride-sharing services match passengers with drivers typically through smartphone apps and provide estimated time of arrival, driver tracking, prepayment, and driver and passenger rating. Under pressure from taxi service providers, regulators and politicians sought to regulate or limit Uber's service. The question of relevance in 2012 was whether ride sharing would disrupt taxi services or if they would coexist.

We analyze data on trips (in thousands) per day from 2010 on yellow taxis and from 2015 on ride-sharing apps.[7] Our analysis (Figure 5d) reveals an increase in cannibalization over time on the rides for yellow taxis due to switchers to ride-sharing services (red line). However, leapfroggers (green line) and dual users (orange line) also contributed to the rise of ride sharing. Thus, ride-sharing services grew by also attracting a whole new segment of consumers. Anecdotally, it seems ride-sharing services have responded to the needs of customers that previously had difficulty availing themselves of taxi services, including low-income consumers and those in remote locations, as well as individuals who are comfortable with app-based technologies. Over time, switchers ended up dominating the other two segments for ride-sharing apps, contributing to the decline of yellow cabs.

The cannibalization of taxicabs by Uber, Lyft, and other such ride-sharing services led to a crisis for taxi services. Medallion prices plunged, and the stock of Medallion Financial (a publicly traded company that manages loans used to purchase taxi medallions in several large U.S. urban markets, including New York) had gone down nearly 49% since Uber raised its Series C funding, according to an analysis done by CBInsights in 2015.

Discussion

Summary of Findings

First, technological disruption is frequent, with dominant incumbents failing in the face of takeoff and growth of a new technologies. However, disruption is neither always quick nor universal because new technologies sometimes coexist as partial substitutes of the old technology. Our generalized model of diffusion of successive technologies can help marketers capture disruption or coexistence due to the presence of a rate of disengagement from the old technology (0–1), which can vary from the rate of adoption of the new technology ($F_{12} \neq F_2$).

[6] Hybrid electric vehicles are powered by an internal combustion engine in combination with one or more electric motors that use energy stored in batteries, combining the benefits of high fuel economy and low tailpipe emissions with the power and range of conventional vehicles. All-electric vehicles use a battery pack to store the electrical energy that powers the motor. All-electric vehicles are zero-emission vehicles because they produce no direct exhaust or emissions.

[7] https://toddwschneider.com/dashboards/nyc-taxi-ridehailing-uber-lyft-data/

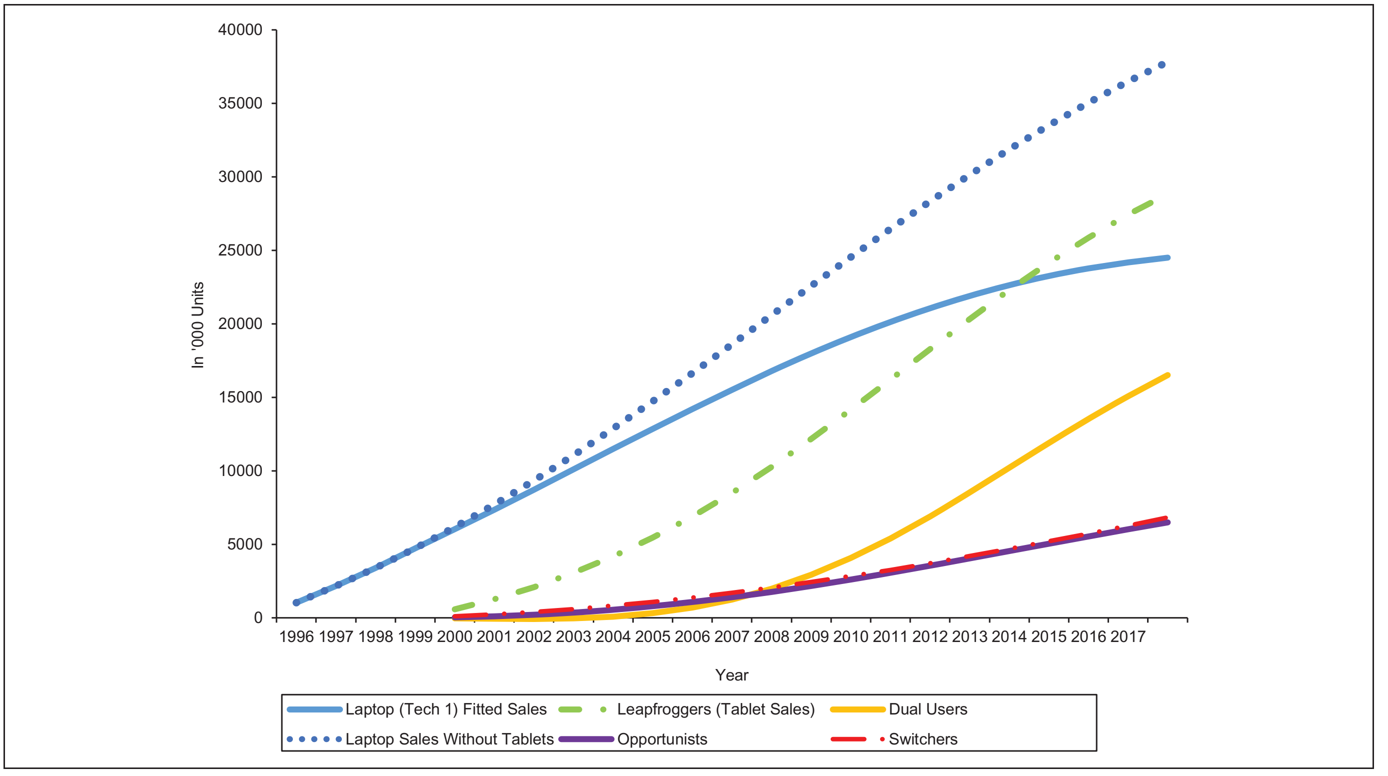

Figure 5b. Decomposition of laptop and tablet sales in the United States.

Second, the model enables a superior fit to aggregate penetration and sales data over prior multigenerational models that do not include such flexibility (i.e., they force F_{12} to equal F_2). Furthermore, an added benefit of the generalized model is that when the rate of disengagement from the old technology equals the rate of adoption of the new, it reduces to a model of multigenerational diffusion.

Third, we identify four adopter segments that account for competition between successive technologies from aggregate data: "leapfroggers" correlate with the growth of the new technology, "switchers" and "opportunists" account for the cannibalization of the old technology, and "dual users" account for the coexistence of both technologies.

Fourth, the generalized model can capture variations in segment sizes across technologies and markets. Leapfroggers form a dominant component of adopters in the early life cycle of a new technology in developing markets compared with other segments. Dual users form a dominant component of adopters in the early life cycle of a new technology in developed markets compared with other segments.

Strategic Implications

The major strategic implications of our findings are as follows: First, many established incumbents stumble or fail due to a takeoff of a new technology. Our model can provide important signals about disruption and survival by estimating cannibalization versus coexistence and forecasting the evolution of four critical consumer segments from aggregate data. Incumbents often wait until the market for the new technology is large enough to be profitable (Christensen 2013) before committing resources to its development. Our analysis suggests that senior managers of strategy and managers of new products should be careful not to underestimate cannibalization by switchers, especially when they dominate dual users, or growth of new technologies due to leapfroggers (especially in developing countries).

Second, despite its frequent occurrence, disruption is not a given when a new successive technology enters the market. Thus, managers do not have to make a stark choice between the two technologies. Disruption may be averted by effectively targeting dual users and by carefully examining factors driving the prolonged (co)existence of the old technology.

Third, the profit implications of leapfrogging and cannibalization vary depending on which firms market which technology. All segments represent a real gain for entrants, as the takeoff of the new technology is always a win. For the incumbent not introducing the successive technology (e.g., HP), the takeoff of that technology is always a loss. Particularly, if the incumbent firm markets the old technology and a new entrant markets the successive technology, then leapfrogging and switching represent a net loss to the incumbent and a net gain to the entrant. For the incumbent introducing the successive technology (e.g., Sony in DVD players), the takeoff of the successive technology is a win if competitors would have introduced it or if the successive technology has a higher margin than the old technology. Leapfroggers are an opportunity loss for incumbents, but switchers are a real loss to incumbents. If

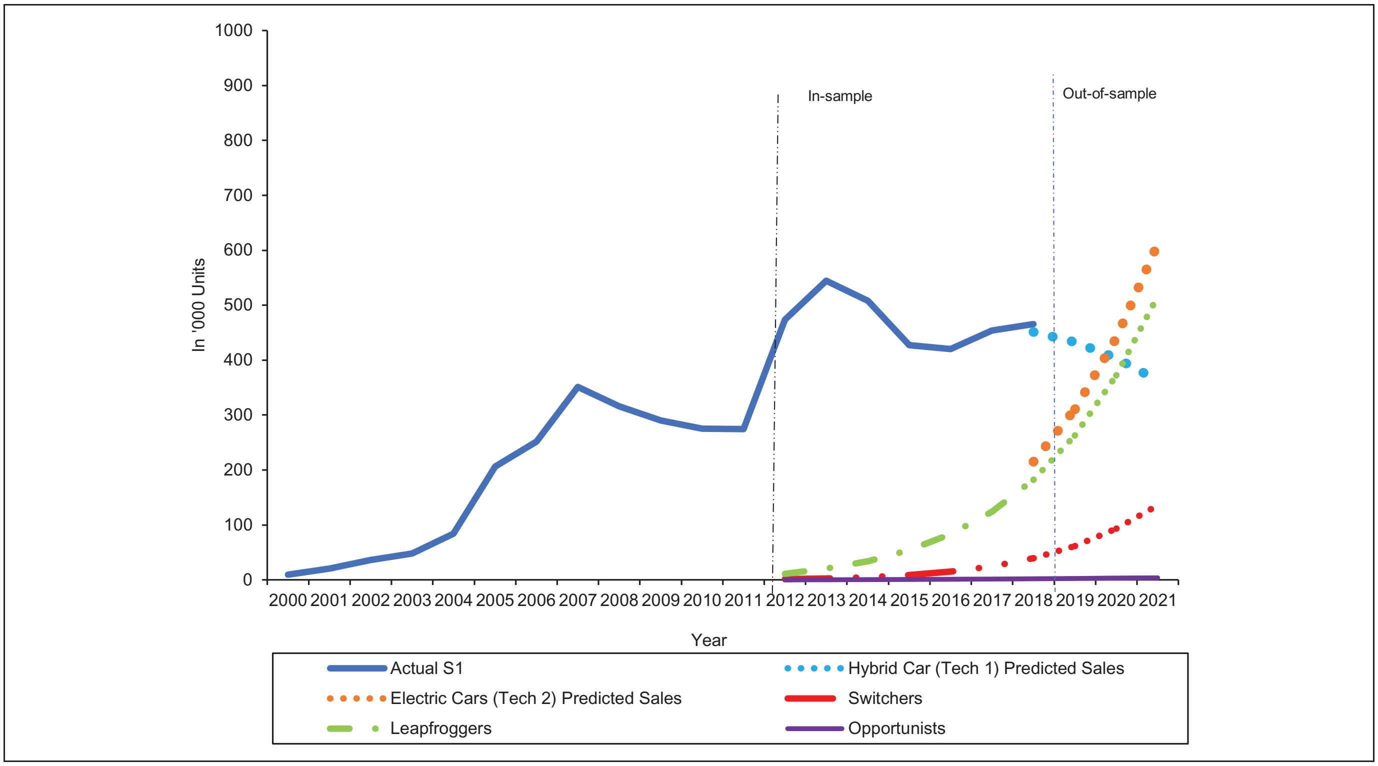

Figure 5c. Prediction in the hybrid and electric car market in the United States.

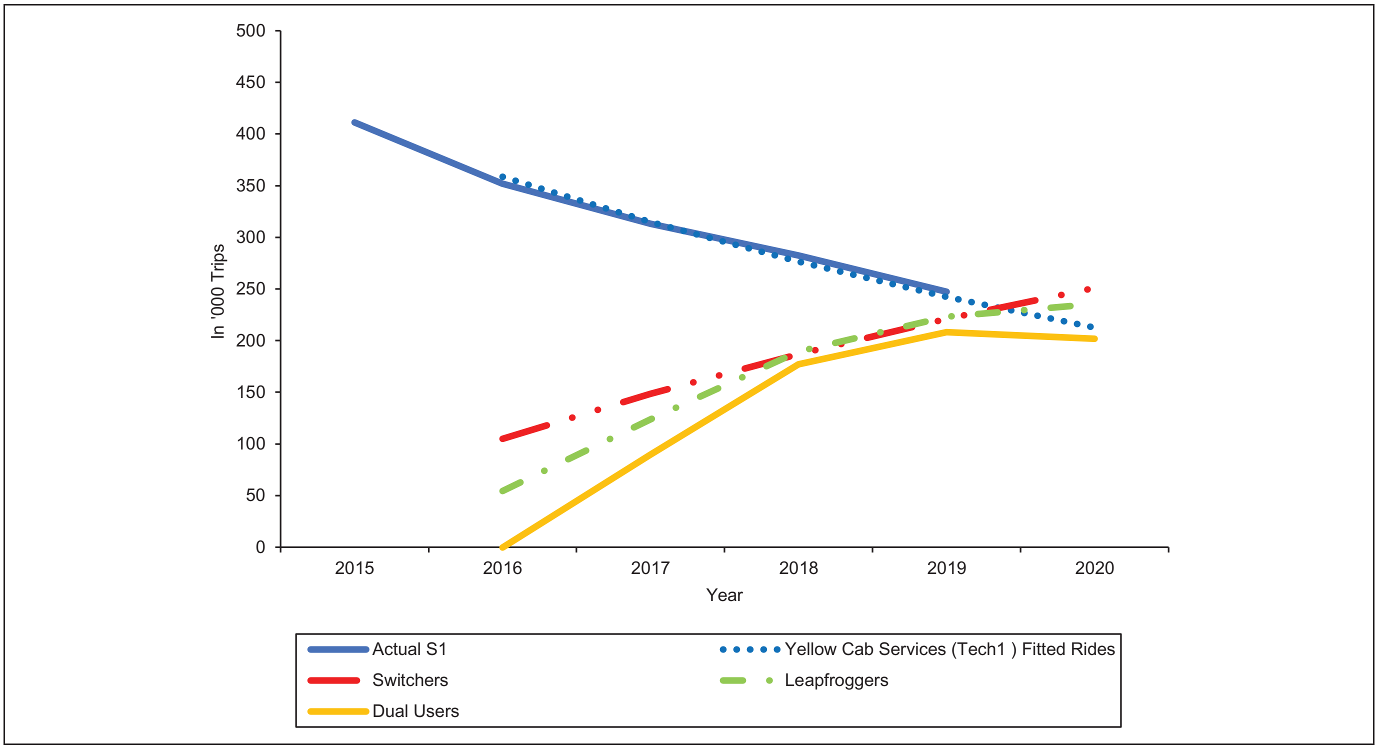

Figure 5d. Decomposition of trips by yellow taxis and ride-sharing services.

Table 5. Adopter Segments, Firm Type, and Market Outcomes in the Presence of Multiple Technologies.

		Firm Type		
Adopter Segments	**Market Outcome on the Introduction of Technology 2**	**Incumbent Marketing Technology 1[a]**	**Entrant Marketing Technology 2[a]**	**Incumbent Marketing Technology 2[b]**
Leapfroggers	Market growth of successive technology	Neutral	Win	Win
Opportunists	Cannibalization of old technology	Lose	Win	Neutral
Switchers	Cannibalization of old technology	Neutral/lose[c]	Win	Neutral
Dual users	Market growth of both technologies	Neutral	Win	Win

Notes:
[a]Assumes that the incumbent (or incumbents) dominated the market for the old technology and entrants pioneered the new technology.
[b]Assumes that the incumbent chooses to enter the new technology market rather than wait on the sidelines.
[c]Neutral for adoption/lose if sales is considered.

the incumbent firm markets both technologies and if the margin on the new exceeds the margin on the old, then switching and leapfrogging represent a net gain to the incumbent. However, if multiple firms market each technology or if margins vary, then the rate of leapfrogging and cannibalization becomes critical to ascertain profitability given the costs.

Fourth, marketers may be able to develop forecasts on the basis of early sales or penetration data of the successive technologies, or from similar contexts, to understand how these various segments may grow (or shrink) over time. Such an understanding can help guide a firm's managerial and economic resource allocation strategies across both technologies over time.

Table 5 summarizes the major strategic implications of this research.

Limitations and Future Directions

This study suffers from several limitations. First, we used aggregate data to test the model because they were abundantly available. As managers and researchers get access to richer, individual customer-level data, they may be able to provide better support to our modeling insights. Moreover, disaggregate choice models can be utilized to address issues such as cannibalization. However, macro diffusion models still have the ability to produce useful macro-level conclusions in ways that micro approaches sometimes cannot. Second, we consider a demand-based view of disruption in proposing the typology of adopter segments. Future research could complement these typologies and data sets with surveys to determine the characteristics of adopters of the new technology versus those who stay with the old technology, as well as what factors influence the size of adopter types. Third, an incumbent may respond to the new technology by making changes in variables such as price, and the omission of such control variables may violate some of the assumptions of the model. All these remain fruitful areas for future research.

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