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RESEARCH ARTICLE

Sequencing innovation rollout: Learning opportunity versus entry speed

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Abstract

Research summary: Our article examines the deliberate creation of learning opportunities in the global rollout of innovations. Some firms launch in only a subset of markets at first, with later launches being conditional on debut-market performance. Such sequencing decreases the downside of potential innovation failure but increases the downside of potential competitive preemption. Consistent with this trade-off, handset makers during the feature-phone era sequence rollout more often when innovations are novel. Also consistent is that sequencing seems to respond to firms' past experience with failure and preemption, and that it begins in markets offering strong signals of success and failure—markets with competing innovations and sophisticated consumers, respectively. Our findings contribute to the understanding of entry strategy and opens avenues for researching intentional organizational experimentation.

Managerial summary: Firms can decide whether to launch innovations little by little or everywhere at once. Trial launches allow firms to test commercial viability and react to outcomes before rolling out elsewhere, but risks that competitors get their first. An immediate global launch, by contrast, reduces the scope for competitive preemption but increases the costs of potential failure. Our article uses data from the handset industry to highlight conditions that shape rollout decisions and examine the debut markets sought out for trial launches. Firms tend to trial novel innovations in particular, and their experience with prior misses as well as flops influences their preference. Trial launches often begin in markets with strong competition and discerning consumers, indicating an initial prioritization of learning over monetization. Opportunities for experimentation during market rollout thus ought to feature in strategic considerations of entry timing.

KEYWORDS

entry timing, firm behavior, global markets, innovation strategy, organizational learning and experimentation, sequential rollout

1 | INTRODUCTION

We explore ways to empirically study variation in firms' global rollout of technological innovations. Rollout decisions are complementary to entry timing (cf., Fosfuri, Lanzolla, & Suarez, 2013; Suarez & Lanzolla, 2007), and concern the approach to target markets at the time of entry. Rollout may range from sequential launches in one small market at a time to simultaneous launches across all markets at once (Griffith & Yalcinkaya, 2018; Holloway, 2017). Toyota and Honda, for example, differed in their rollout of battery technology that enabled hybrid cars in 1999. Toyota launched in Japan first, with the possibility to amend or scrap its Prius model before launching elsewhere. Honda launched its Insight model simultaneously across markets, including the United States (Reinhardt, Yao, & Egawa, 2006).

Sequencing rollout trades off learning and speed (Stremersch & Tellis, 2004). A sequential rollout offers opportunities to learn from debut markets about the wider commercial viability of an innovation, and to cap or modify further rollout in cases of failure. At the same time, it allows for competitive preemption elsewhere. A simultaneous launch may preempt competitive offerings but allows for the greater cost of global failure. Sequential innovation rollout can thus be conceived as a learning opportunity (Eggers, 2012; Lapré & Nembhard, 2011) that comes at the expense of speed to market. But although recent research on the phenomenon suggests firms do learn from sequential rollouts, with the success in early-launch markets determining the probability of later-market launches (Eaton, Eslava, Kugler, & Tybout, 2007; Holloway, 2017), it remains unclear under which conditions firms deliberately create such learning opportunities, the subject of our study.

The setting for analysis is the mobile-handset industry during the feature-phone era (Giachetti, 2013; Koski & Kretschmer, 2010). During this period, most big handset makers were active globally. They could launch individual hardware-feature innovations such as Bluetooth and Wi-Fi on phones everywhere at once, or to roll them out market-by-market. Competitive preemption was a constant concern in this fast-moving industry, as was costly innovation failure. For the feature-phone years 2004–2008, our data enable us to identify over 300 separate firm-feature rollouts, roughly half of which followed a strictly sequential launch protocol.

Using alternative specifications for measures and models, we find support for innovation novelty increasing sequencing, consistent with expectation that firms launch sequentially in part for learning purposes. Rollout sequencing also appears sensitive to firms' experience of both commission errors (prior innovation failures) of omission errors (prior pre-emptions). We further find that sequential rollouts more likely debut in markets with characteristics that generate informative signals of commercial viability. Debut-market competition in the focal feature innovation vets new offerings and provides reliable signals of success. Debut markets' consumers at the focal-innovation frontier have the sophistication to best utilize the latest functionality improvements and provide reliable signals of failure. The findings point toward deliberate experimental learning and are robust to a variety of alternative explanations.

The article offers two principal contributions. First, we add to the entry literature (Fosfuri et al., 2013; Suarez & Lanzolla, 2007) by qualifying the entry phenomenon, showing that ostensibly early entry in one part of the world might be a late entry when viewed from another. Two concurrently observed innovation entries could be part of very different strategies for full-scale market presence. Sequential innovation rollouts with a learning focus generate entries in fewer and different places than simultaneous rollouts with a focus on monetization or market share. Informative debut markets for sequential rollouts are often ones that standard competition theory suggests had best be avoided (Anand, Mesquita, & Vassolo, 2009; Fuentelsaz & Gómez, 2006).

Second, we add to literature on organizational learning (Argote & Miron-Spektor, 2011; Argote & Todorova, 2007) by enhancing the understanding of deliberate decisions to learn. Learning can occur serendipitously, but often results from systematic efforts at collecting information (Huber, 1991). Despite a wealth of knowledge about how and what firms can learn, the learning literature remains relatively quiet on when firms might deliberately decide to do so (Bingham & Davis, 2012; Lapré & Nembhard, 2011). Our examination of the learning-speed trade-off in innovation rollout addresses this gap and provides unique insights into when and how firms intentionally create learning opportunities. Such insight furthers understanding of how organizations negotiate classic decision tradeoffs that include learning, such as those between exploration and exploration (Lee & Puranam, 2016; Wilden, Hohberger, Devinney, & Lavie, 2018), commitment and flexibility (Klingebiel, 2022; Posen, Leiblein, & Chen, 2018), and risk of making commission and omission errors (Klingebiel, 2018; Maslach, 2016).

2 | LEARNING OPPORTUNITIES IN INNOVATION ROLLOUT

2.1 | Entry decisions and rollout

The entry literature is rich and rallies around the performance implications of early and late entry (for comprehensive reviews see Fosfuri et al., 2013; Lieberman & Montgomery, 2013; Suarez & Lanzolla, 2007). Inferences about the impact of various isolating mechanisms are debated (Dykes & Kolev, 2018; Kalyanaram, Robinson, & Urban, 1995; VanderWerf & Mahon, 1997), however, in part due to the growing realization that entry itself is a strategic consideration and driven by many of the same factors that also drive performance.

Firms deliberating entry may, for example, choose to enter more readily when markets match their capability base (Lee, 2008) and technology-investment history (Kapoor & Furr, 2015; Moeen, 2017). They may also align entry choices with their business-model orientation (Gomez, Pérez-Aradros, & Salazar, 2019; Markides & Sosa, 2013) as well as the intensity (Robinson & Chiang, 2002) and scope (Klingebiel & Joseph, 2016) with which they pursue innovative endeavors. This underscores the usefulness of first understanding how firms actually make entry decisions.

Studies of entry decisions become especially relevant when these are made repeatedly. Recurring decisions include introducing further products into established markets (Ethiraj & Zhu, 2008) or niches of the same market (Greve, 2000), updating product generations (Franco, Sarkar, Agarwal, & Echambadi, 2009), and bolting new technological features onto existing product designs (Paulson Gjerde, Slotnick, & Sobel, 2002). Frequent entry enables the study of what firms aim to achieve across multiple entries (e.g., Klingebiel & Joseph, 2016) as well as what they may want to achieve with some but not others (e.g., Kim, Kim, Miller, & Mahoney, 2016). Our aim is to extend knowledge about the latter: we argue that entry occurring as part of a more sequential rollout is qualitatively different from one occurring as part of a more simultaneous rollout, and we examine how and when one entry mode differs from the other.

Our focus is the global rollout of product-feature innovations, which can vary between a strictly sequential market-by-market launch pattern and a fully simultaneous all-markets-at-once pattern. Such variance may also exist at the level of firms expanding internationally (Delios & Henisz, 2003) as well as the level of products meant for a global audience (Holloway, 2017). Both ends of the rollout spectrum are potentially desirable, with the critical distinction being the downside of failure and preemption, respectively, that each embodies (Stremersch & Tellis, 2004).

2.2 | The trade-off between learning and speed

Sequencing innovation rollout offers opportunities to learn (Holloway, 2017). Launching in a subset of addressable markets generates signals, which reduce the residual uncertainty about an innovation's wider commercial viability that remains after R&D. Thus, sequential rollouts constitute series of experiments, whereby firms accumulate knowledge as they proceed. Key learnings may include how likely the particular innovation finds a receptive customer audience as well as how it holds up against competitive offerings. If an innovation fails in debut markets, firms might make adjustments prior to further rollout, or prevent further rollout altogether and allocate resources to other, perhaps more promising alternatives. By choosing to sequence more, firms can deliberately minimize the downside potential of failing big in a worldwide launch, at the expense of delaying the eventual full-scale rollout of the innovation. While sequencing caps the potential costs of failure, it slows global rollout and potentially cedes markets to competitors launching more quickly.

Simultaneous rollout of innovations in all addressable markets, by contrast, offers speed of monetization. The more simultaneous the rollout, the greater the chances of beating competitors to more markets. Entry before more competitors arrive may generate longer and greater revenue premiums for the innovation (Klingebiel & Joseph, 2016) as well as potentially persistent early-mover advantages (Lieberman & Montgomery, 2013). Not all innovations are successes, however. Simultaneous rollout amplifies not only the upside of success, but also the downside of failure. At the extreme, simultaneous rollout involves contemporaneous worldwide entry, precluding opportunities to learn from one market to the next. Rollout costs are thus incurred everywhere regardless of eventual success, including costs pertaining to customization, channel arrangements, marketing campaigns, and inventory.

The learning-versus-speed tradeoff is pervasive (Griffith & Yalcinkaya, 2018) but usually hard to observe. The global handset market is an exception: demand trends are global but sales and marketing arrangements are made at the country level. Initial launch patterns thus contain meaningful variance in the degree to which local learning is attempted prior to committing to more global launches. Our article can thus provide insights into the conditions under which firms deliberately decide to sequence innovation rollout for the purpose of creating learning opportunities, and how they would structure such learning opportunities to best capture signals of potential success or failure. We do not suggest sequencing occurs solely for the purposes of learning, nor that sequential geographic rollout is the only form of learning opportunity available to firms. Rather, we posit that the learning-speed trade-off in rollout sequencing renders systematic rollout patterns that have theoretical implications for understanding firms' deliberate creation of learning opportunities.

2.3 | Learning about novelty

Deliberate creation of learning opportunities likely increases when the advantages of learning exceed the need for speed. This is more likely when innovations that are newer to the market. With few other firms having launched a feature already, commercial viability cannot easily be inferred from competitive observation. Little prior market vetting means greater scope for surprise updates to expectations of commercial viability (Conti, Gambardella, & Novelli, 2013). Therefore, the sequencing of more novel innovations can avoid potentially greater failures than sequencing less novel innovations.

At the same time, the preemption threat is less immediate for more novel innovations than less novel innovations. This is because full-scale global rollout is less urgent when few competitors are ready to enter, either because they are not yet able to develop the innovation or are similarly hesitating to commit to wide-scale rollouts. For more novel innovations, the learning benefit of being able to prevent costly global failures thus likely outweighs the speed benefit of avoiding competitive preemption.

That firms sequence the rollout of more novel innovations would also be consistent with a real-options logic (Klingebiel & Adner, 2015). As the value of a low-cost entry option increases when outcomes are less predictable, it more likely outweighs the potential costs of preemption (Folta, 1998). Firms following a real-options logic might, for example, enter more novel markets through partnerships rather than acquisitions, so as to reduce the downside of potential failure (Chang & Rosenzweig, 2001; Kogut & Chang, 1996).

The speed of rollout might be a bigger concern for less novel innovations (i.e., features already pioneered some time ago). More information to discern commercial viability is available for these and the need for additional learning is smaller. As both a focal firm and competitors may arrive at similar conclusions about commercial viability when viability can be more easily gauged, following early-movers through sequential launches stand to forfeit more of the remaining markets to competitors. Therefore, the need for speed is greater for the rollout of less novel innovations, more likely outweighing a reduced need for learning. Therefore, our baseline hypothesis is:

Hypothesis (H1). *Rollout sequencing increases with innovation novelty.*

2.4 | Firms' preference for learning

Decisions to create learning opportunities may be sensitive not just to innovation-specific considerations such as novelty. They may also be informed by firm-specific tendencies to opt for learning over speed in innovation rollout. Preference for either likely develops as a path-dependent process (Einhorn & Hogarth, 1978): decision-makers' impression of the relative value of learning and speed stands to be informed by their record of prior outcomes. Firms differ in the degree to which they have commercialized innovations that proved unsuccessful (commission errors), and the degree to which they have not brought to market the innovations that proved successful for others (omission errors). This history of making commission and omission errors might thus influence their general propensity to countenance the possibility of making such errors again.

Recent research (Dye, Eggers, & Shapira, 2014; Klingebiel, 2018) building on the behavioral theory of the firm (Cyert & March, 1963; Gavetti, Greve, Levinthal, & Ocasio, 2012; Greve, 2003) suggests that firms' past experience influences their propensity to take on exposure to commission and omission errors, respectively. Even if some firms might be better ex ante than other firms at picking winners and rejecting failures, no firm can eliminate risk entirely, and thus still needs to decide whether it prefers exposure to the first or second type (Garud, Nayyar, & Shapira, 1997). So if firms, no matter how savvy, made more of one type of error than the other in the past, they likely try avoid this type going forward (Dye et al., 2014; Klingebiel, 2018). Past errors sensitize firms and make them attempt to rectify the problem by shifting their relative preference for the risk of making errors of commission versus the risk of making errors of omission. Such risk-type preference shifts in response to error feedback might be observable in the rollout pattern of our mobile feature innovations. Commission errors and omission errors can occur independent of each other and both sway firms' impression of the relative value of learning and speed in innovation rollout.

Commission errors likely drive sequencing. A handset maker with a history of releasing unsuccessful innovations is sensitized to the downside of failure. Therefore, we expect this handset maker to place greater emphasis on ascertaining the commercial viability of subsequent innovations than handset makers with less of a Type-I error history. With learning about commercial viability taking on greater importance, sequencing becomes more desirable. We predict firms that previously launched unsuccessful innovations to more likely create the learning opportunity that sequencing offers:

> **Hypothesis (H2).** *Rollout sequencing increases with firms' experience of commission errors.*

Omission errors have the converse effect. Even if omissions can have many reasons, and decision makers might not always feel at fault, a record of missing hit features likely sensitizes firms to the foregone-income implications of competitive preemption. We expect handset makers with a record of omission errors to place greater emphasis on beating the competition to market than handset makers with less of a Type-II error history. With speed taking on greater importance, sequencing becomes less desirable. We expect firms that missed out on successful innovation to more likely forego the learning opportunity that sequencing offers:

> **Hypothesis (H3).** *Rollout sequencing decreases with firms' experience of omission errors.*

2.5 | The strength of learning signals

The choice of debut markets in sequential rollouts qualifies the creation of learning opportunities. Debut markets vary in the degree to which launching there provides informative signals of innovations' wider commercial viability. Therefore, sequential rollouts will not only look for debut markets where learning is cheap (Bingham & Davis, 2012; Sitkin, 1992), such as markets that are small or a firm's home. The informativeness of debut markets stands to matter too (Cochran, 1953; Shannon, 1948). Our predictions focus on this signal-strength dimension to debut-market choice.

The more reliable a debut-market signal, the more likely correct is the decision to continue or abort further launches. The similarity of a debut market to later launch markets naturally adds to such reliability—the handset industry is largely global, with similar product-demand structures across countries, which enables some transferability of learning. More interesting from a theoretical perspective are two characteristics of debut-markets that increase the reliability of signals for global-market commercialization of innovations: characteristics that make it hard to succeed (easy to fail) offer more reliable signals of success, while characteristics that make it hard to fail (easy to succeed) offer more reliable signals of failure (Bohn & Lapré, 2016; Shapira, 2020).

One of the most obvious hurdles to success is competition. A firm intending to learn from a sequential rollout might seek out the challenging test environment of markets with competition in the focal innovation. Success in such competitive markets signals that later success in benign markets is probable. The reverse is less likely to be true and thus inconsistent with a learning intention. Launching in a market without innovation competition may be attractive on its own (Fuentelsaz & Gómez, 2006; Greve, 1998, 2000; Haveman & Nonnemaker, 2000), but it provides little confidence in the probability of succeeding in markets with potentially superior competitive alternatives. Similarly, while during development firms might seek out safe environments to nurture and fine-tune their fledgling innovations before these are exposed to the forces of market selection (Greve, 2000), the rationale changes after development: to generate reliable early signals of the wider success of the innovation, challenging environments are the more informative testbeds.

The competitive rigor imposed by rival offerings thus minimizes the chance of generating false positives, and may additionally provide inspiration for how to further improve quality. The face validity of this proposition is supported by anecdotal evidence: In an interview, Procter & Gamble's CEO A.G. Lafley stressed the signal quality of success against tough competition. For some skin-care innovations, Lafley said "you better be in Paris, and you better be in Tokyo." Before launching an innovation in other markets, Procter and Gamble had "cut our teeth on very good competition" (Bartlett, 2004). The idea is not that observing competitors also affords opportunities to learn (Baum & Ingram, 1998; Greve, 2011; Madsen & Desai, 2010). Firms benefit from engaging in vicarious learning anyways, regardless of whether or not they decide to launch in a market. Our argument is rather that a learning rationale for debut-market choice appreciates that exposing a new innovation to competing offerings is more informative than selling in markets without such rival offerings. With later rollout markets sharing at least some of all the factors that make success difficult in debut markets with competition in the innovation, seeking out such debut markets promises greater learning. This competitive success-signal strength is the basis for our fourth prediction:

Hypothesis (H4). *Sequential rollouts begin in markets with more competition in the focal innovation.*

Sequential rollouts may further seek reliable signals of failure. The dimensions relevant for reliable signals of failure need not be those of success. For example, a lack of competition does not automatically make failure difficult. The lack of competition in a market might indicate that consumers are uninterested, making it probable that the focal firm fails too. Instead of competition, firms are likely to consider other dimension that are relevant for generating reliable signals of failure in debut markets. One obvious market in which it is relatively harder to fail is a firm's home market or the market in which it has a high market share. Given consumer loyalty to brands, even lackluster innovations might easily succeed in markets the firm dominates. Market dominance, however, is an unsatisfying dimension for testing our theory, because it embodies other rollout considerations too (strong distribution infrastructure, for example) and because it does not vary at the innovation level.

Instead we focus on a dimension central to the marketing literature. Consumer sophistication refers to the domain-specific readiness of consumers to adopt new products (Goldsmith & Hofacker, 1991; Hauser, Tellis, & Griffin, 2006). Markets with sophisticated consumers would be those that show high levels of usage of the predecessor innovation most closely related to the focal one.

The signals of failure that sophisticated consumers can provide is one of the reasons why software companies, for example, tend to solicit cohorts of early adopters that serve as beta-testers for new products. Similarly, in the aforementioned Procter and Gamble example, the CEO A.G. Lafley underscored the signal quality of feedback from sophisticated consumers of creams with anti-aging ingredients: "Japanese women are incredibly demanding. They are incredibly discriminating. They notice and appreciate product differences and are willing to pay for them" if they like them (Bartlett, 2004). In our context, handset executives mentioned that for camera innovations, for example, South Korea contained more customers taking multi-megapixel pictures then Brazil.

In this stylized example, launching an advanced camera feature in Brazil would generate an unreliable signal of failure, because Brazilian consumers might refrain from buying it simply due to insufficient readiness, be it due to local use preferences or infrastructure constraints. To handset makers, Brazil could be an attractive market in the sense that the camera innovation offers customers there a more perceptible improvement on prior art, driving local sales expectations. But a negative reaction by Brazilian customers to the innovation would offer few clues about sales expectations in markets with more advanced consumers. Korean consumers, by contrast, are ready in principle for further camera features. If they shun some of them, it is because of an informed judgment about their efficacy. A feature that fails here might do so for reasons that will eventually apply to Brazil too, once Brazilian customers reach the same level of readiness.

Since launching in more markets with more sophisticated consumers makes success more likely, failure in such markets provides a more conservative signal than failure in markets with less discerning consumers. As industry lifecycles make markets with less sophisticated consumers reach the sophistication of consumers in debut markets eventually, debut lessons stand to be informative for later launches. A possible brake on this effect would be the emergence of discontinuous innovation after a sequential debut and before later wide-scale rollout (Christensen & Bower, 1996). Yet, to the extent that firms sequence rollout with the intention to create learning opportunities, whether or not disruption later upends these plans, we expect to see a preference for debut markets where consumers are furthest along the innovation-specific sophistication frontier. Therefore, we predict:

Hypothesis (H5). *Sequential rollouts begin in markets with more sophisticated consumers for the focal innovation.*

3 | METHODS

3.1 | Empirical setting

We study the rollout patterns for innovations in the handset industry during the feature-phone era. This period dates back to the early 2000s (Giachetti, 2013), at a point where most mobile handsets delivered high-quality voice transmission on the basis of which customers were no longer able to discern between competing products. To differentiate, ancillary hardware features became handset makers' main focus of innovation, leading to a proliferation add-on functionality including Wi-Fi, Bluetooth, cameras, gaming interfaces, fingerprint scanners, dual sim cards, memory, and much besides (Giachetti & Marchi, 2010; Klingebiel & Joseph, 2016). This mode of competition lasted until about 2010, beyond which the source of differentiation moved toward software, including the nexus of operating system and app store—Apple's iPhone and other smartphones had together gone beyond a 10% share of handset sales by 2011 (Giachetti, 2018).

By the feature-phone era, the handset industry had gone global, with similar sets of competitors in many countries. With some regional variation in market dominance, products of the industry's main firms such as Nokia, Motorola, Samsung, LG, and Sony Ericsson could be found virtually anywhere with mobile phone reception. Handsets, like other electronic goods, could be manufactured centrally and distributed globally. Sony Ericsson, for example, operated production lines in Mexico and India, with the output being sold there as well as at home in Sweden, and further afield in Japan or the United States, for example (Chang, 2011). When developing new features, handset makers thus target markets beyond their own.

Since technological features were the locus of innovation, the appropriate unit of analysis for our work is also at the feature level, not the phone level. Although firms might offer innovations on multiple handsets of different names, colors, and form factors, they organized innovation around feature-specific projects (Klingebiel & Joseph, 2016). Adding new technological features to future products would typically take between 1 and 2 years.

Few isolating mechanisms existed as handset makers were technology takers (Paulson Gjerde et al., 2002), integrating off-the-shelve components provided further upstream. Although some integration solutions were patentable, rival firms could not be precluded from also adding Wifi technology to their handsets too, for example. Access to production inputs was typically not privileged and few network effects could be expected (Giachetti, 2013) prior to the smartphone era. Most innovation decisions were thus imitative or based on expectations of eventual imitation, with monopolistic returns attainable only if firms got it right before competitors did, and only for as long as it took competitors to launch similar features (Giachetti, Lampel, & Li, 2017).

The frequency of imitation meant that first-movers were not necessarily first everywhere. An often cited example is the first camera phone, which was pioneered by Kyocera in Japan, but launched first in the United States by Sanyo (Goggin, 2006; O'Regan, 2018). Our data (see below) also bears out this risk of preemption: The global pioneer of a feature innovation was the first to launch in markets other than the initial one in only 39% of cases. In the other 61%, fast-moving competitors would get there first.

After feature development, handset makers would decide about the eventual approach to the global market. Development costs were sunk, but they still had discretion over costs associated with rollout. At firms like Nokia, it was toward the end of the development process, when production lines had to be reserved and first mass orders of materials placed, that decisions were made about the order sequence of launch markets for the innovation (Doz & Wilson, 2018).

For rollout, the main worry was whether or not a feature would be successful in the global market (development had already reduced technical uncertainty). By one industry benchmark, only 26% of all features ever launched were considered successes ex post (Klingebiel & Joseph, 2016). Rolling out feature innovations would resolve such commercial uncertainty. The later such rollout began, the more could already be gleaned from competitors about general market acceptance. Yet, whether or not a firm's specific implementation of a feature innovation would find success would ultimately remain a question of trying. Learning from rollout could lead firms to refrain from further launches or modify their offerings.

Innovation rollout had to be organized on a country-by-country basis. Each country had its own set of distributors and retailers, and carriers incorporated locally even if they share a global brand. Vodafone, for example, might test handsets in regional centers, but made decisions locally about the kinds of phones to be included in the local offer catalogue. In addition to negotiating local distribution agreements, handset makers had to customize hardware (e.g., frequency bands, keyboards) and software (e.g., Java MIDlets, operator settings) for each country. Therefore, the usual economies of scale in R&D and manufacturing would not extend to distribution. And since the local cost of distribution was mainly linked to market size, market concentration, and carrier bargaining power, it was largely unrelated to innovation-specific factors that we propose determine the strength of learning signals generated by selling in a market.

Even before accounting for lost opportunity in capacity-constrained production, irrecoverable distribution costs easily outweighed those for feature development (Klingebiel & Esser, 2020), creating a substantial downside to launching in multiple markets at once. Failure made it difficult to recoup the fixed costs of customization, arranging sales channels, and promoting relevant phones. Initial distributor inventory might go unsold, and material ordered in advance might go unused if production were curtailed. Together with the reciprocal downside of rolling out a successful feature too slowly and being preempted by competitors, such costs created a learning-speed tradeoff in decisions about the global rollout of innovations.

3.2 | Dataset

We use a handset dataset compiled from GfK and Informa market research panels and extensively cross-checked by our research team. The dataset contains phone sales and characteristics at a monthly country level. Data collection was at the point of sales, allowing us to cleanly identify when a particular feature was first sold in a given location. The data cover the years 2004–2009, allowing us to code entry for features that firms began to launch in 2004–2008.

Our sample period contains the full population of 50 feature innovations validated in prior studies (Klingebiel & Joseph, 2016). We spent significant time and effort triangulating and verifying whether handset makers launched any of these in each of 13 country markets: Brazil, China, France, Germany, India, Indonesia, Italy, Japan, Korea, Russia, Spain, United Kingdom, and United States. These 13 markets were the world's biggest and collectively constituted about 60% of the total world market (ITU, 2015). They are thus representative of the global market and, crucially, include all major country markets that were sufficiently advanced to be meaningful for innovation rollout.

Most innovations that were successful in early markets eventually ended up in most markets, underlining the global nature of the handset industry. Furthermore, the industry value chain was similarly structured in all 13 markets in that handsets were sold through both numerous retail outlets and a handful of locally incorporated carriers. Negotiations were country-specific, and the favorable bargaining situation reduced the chance that any of our globally active firms could be barred from launching a feature innovation in a particular target market (Giachetti, 2013).

We made sure to assign innovations to the originators, not contract manufactures, and we carefully adjust for M&A activity. We then selected the most international firms for analysis. For this we require handset makers to be established in international markets for at least a year before studying their entry behavior there. This ensures that our study is about innovation entry, not firm entry, which would otherwise give rise to a host of other considerations (Delios & Henisz, 2003). To make the international cut, we also require handset makers to have launched more than 10 handsets in at least two country-markets, on average, during our observation period. This gives us 29 globally active firms. Twenty-one of the selected firms were headquartered in Asia, four in Europe and four in North America. Stricter internationality criteria reduce the set of eligible firms but roughly maintain the continental split, reflecting the geographic location of the industry leaders at the time. Together, the 29 firms were responsible for 92% of worldwide sales over the observation period (ITU, 2015). Each of the 29 firms launched a subset of the 50 possible feature innovations, captured at the monthly level. This gives us 382 firm-feature rollouts and 1,802 firm-feature-market launches (when we lag our variables, we lose some of these observations).

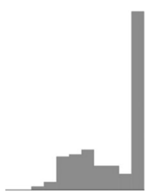
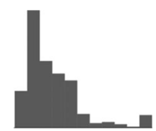
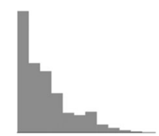
Although in this article we examine firms' decisions to create opportunities for learning through sequential entry, and not whether firms actually do end up learning from such opportunities, our data provides some evidence that they do in fact learn from one market to the next. In particular, features rolled out sequentially that are unsuccessful in initial markets do not spread as far as sequentially rolled out successes. Among the firm-feature rollouts in our data that were initially launched one market at a time, successful features on average made it to two more country markets than unsuccessful ones (see below for variable definitions). Conditional on sequential progression to five markets, failing features were also 28% more likely than winning features to be launched on a different handset in the fifth market. Such modifications show that, even if sequential rollouts do not always terminate after evidence of failure, they would often lead to modifications in the way innovations were delivered to the customer. By contrast, if markets are targeted simultaneously, there naturally is no opportunity to respond to intermediate outcomes, be it through delivering the innovation on a different handset or stopping the innovation rollout entirely.

3.3 | Variables

3.3.1 | Rollout sequencing

The dependent variable for testing hypotheses (H1)–(H3) is to capture variation in the degree to which handset makers begin the rollout of a feature innovation by creating learning opportunities at the expense of potential competitive preemption. This design objective requires a number of choices, none of which is indisputable. Therefore, we explore results' sensitivity to such choices: Table 1 summarizes the facets of five principal specifications (RS1–5) of a rollout-sequencing variable. RS4 is the specification in our main analyses (bold in Table 1).

TABLE 1 Rollout sequencing—DV designs

Specification	RS1 $\frac{\text{Releases}}{\text{Countries}}$	RS2 $\frac{\text{Releases}-1}{\text{Countries}}$	RS3 $\frac{\text{Releases}-1}{\text{Countries}-1}$	RS4 $\frac{\text{Releases}}{\text{Customers}}$	RS5 $\frac{\text{Releases}-1}{\text{Customers}}$
Advantages	Simple specification	Simple specification	Prior use (Holloway, 2017)	**Construct validity**	Closer to prior use
Disadvantages	Countries not i.i.d., low variation	Classifies failed sequential rollouts as simultaneous	Omits 1/3rd of observations, success bias	**Limited comparability with prior use**	Classifies failed sequential rollouts as simultaneous
Observations (rollouts)	316	316	216	**316**	316
Groups (features)	49	49	46	**49**	49
Values	30	30	28	**202**	181
H1 coefficient (*p*-value) model IIIB	.001 (.36)	−.005 (.00)	−.000 (.29)	**−.013 (.00)**	−.005 (.00)
H2/H3 coefficient (*p*-value) model IIIB	.026 (.09)	.064 (.03)	.066 (.02)	**.187 (.10)**	.079 (.03)
Distributions					

RS1–5 all set the number of separate releases in relation to the extent of the global market targeted with those releases. Smaller values indicate a more simultaneous feature rollout, larger values a more sequential rollout. As input for the numerator of this ratio, we count releases occurring in the first 12 months[1] of rollouts that began within 3 years[2] of the global pioneering date for a feature. We consider releases as distinct if they occur by a month or more apart.

A design choice for the numerator made in a study of the movie industry (Holloway, 2017) removes the first release from the operationalization (RS2, RS3, and RS5 in Table 1). This treats single-release rollouts as simultaneous, thus viewing such releases as targeting isolated markets only. An alternative, reflected in our main measure RS4 (and also RS1), has single-releases at the sequential end of the dependent variable, which is informed by handset practitioner testimony about the global nature of handset innovation, and the industry fact that many innovations fail and thus never advance beyond their initial launches (Klingebiel & Joseph, 2016).

For the denominator of the sequencing variable, it is important to capture the extent of the global market that firms target with the observed release events. This could simply by proxied by counting countries (RS1–3). Handset makers' risk–reward calculations, however, do not readily correspond to the country unit. A key issue is that countries are not identically distributed, with China containing an order of magnitude more addressable customers than Spain, for example (see Online Appendix Table E). Firms, therefore, likely appreciate the greater risks and rewards of launching in the former. What matters are the number of addressable consumers. RS4 and RS5 are thus based on a measure of active postpaid and pre-paid sim cards (ITU, 2015), in 100 m. Using addressable customers is to more closely align our operationalization of the dependent variable with the decision phenomenon of sequencing that it is supposed to reflect.

A further design consideration is whether to include single-step rollouts in the sample for analysis. The Holloway (2017) study of movie rollouts does not, arguing that single rollouts are ambiguous: features were either intended for one market only (simultaneous = sequential) or for many but failed early on (sequential). The specification of the denominator in RS3 duly omits such potentially ambiguous cases. In the global handset industry, however, few feature innovations are ever intended for small markets only, so the concern appears less relevant. The chance of misclassifying the sequencing of an intentionally single-market innovation is thus small for RS1, RS2, RS4, and RS5. It removes the need to omit observations from our analysis, guarding against a selection bias toward successful launches.

In all, we chose RS4 as the primary measure given its validity for the handset industry. See Online Appendix Table C for a comparison of regression results for each of the different design alternatives.

3.3.2 | Debut market

The second dependent variable, for testing (H4) and (H5), identifies the initial launch country in sequential feature rollouts (simultaneous rollouts, by definition, have no market-ordering of

[1]The results reported in Table 2 are robust to alternative measurement-window lengths of 7–13 months.

[2]Very late releases of preexisting features may have little to do with innovation, as elaborated by Klingebiel and Joseph (2016).

entry). The variable is a simple dummy, indicating whether or not the country was the market of first introduction. We limit the analysis to strictly sequenced rollouts, that is, those cases where features were launched in no more than one market per month. Fifty-one percent of all firm-feature rollouts in our data qualify as fully sequential.[3]

Such strict sequencing provides the strongest possible indication that firms want to learn, qualitatively distinguishing firms that create learning opportunities from those that do not. Our models remain largely robust when we relax this in later robustness checks, including where only the first launch need be a single market (with varying lags to the second launch) and where, instead of looking at single markets necessarily, we allow for increasingly large blocks of markets that saw the first release, gradually including more firms with a lower interest in learning. Results also remain consistent when predicting the second market instead of the debut market, with a conceptually reassuring decrease in explanatory power (see Online Appendix Table F).

Each feature could theoretically have been first launched in any one of the 13 country markets. This means that for each firm-feature, the dependent variable contains one firm-feature-market observation with the value of 1, and 12 observations with a value of 0. The 187 strictly sequential rollouts in our data thus constitute an estimation sample of 2,431 observations. Debut choices vary considerably, with all 13 markets seeing debut entries. The average country saw 15, with Japan experiencing the most with 61 debuts and Spain the least with 1 debut (see Online Appendix Table E).

3.3.3 | Independent variables

Our independent variable for testing (H1) is *innovation novelty*, for which we use two alternative specifications. The first captures the time elapsed since the entry of the global feature pioneer. This can range between 0 months for pioneers and 35 months for late entrants. The interpretation is that the longer a feature has been on the market somewhere, the more information a focal firm can glean from the pioneer's experience, reducing uncertainty about the commercial viability of the focal feature (Dahlin & Behrens, 2005; Klingebiel, 2018). To check whether our measure of novelty is sensitive to the number of competitors already offering the feature innovation, rather than just the time on the market, we also count how many of the world's firms had already adopted the focal feature by the time of a firm's first launch. This global novelty measure ranges from 0 to 23. The findings we present below are robust to this alternative proxy for novelty.

Omission-error experience (H3) is a count of all the innovations not launched by the focal firm in the preceding year that turned out to become industry successes. These are innovations that generated local peak revenue premiums in excess of €2m per month (average revenues from phones with the focal feature and revenues from otherwise comparable phones without the focal feature). Industry practitioners used this threshold for identifying innovative successes; so did prior studies in the field of management (Klingebiel, 2018; Klingebiel & Joseph, 2016). It forms our measure of omission errors.

Conversely, *commission-error experience* (H2) is a count of all feature innovations launched by the focal firm in the preceding year that did not become commercial successes (and also did

[3]The proportion of strictly sequential rollouts remains relatively stable over time: 60% in 2014, 51% in 2015, 45% in 2016, 50% in 2017, and 49% in 2018.

not become permanent handset fixtures). This forms our measure of commission errors. Conceptually, foregone hits and adopted flops are not completely independent, since a firm's innovation-portfolio breadth and innovation-selection quality can drive both at the same time. But they are also not completely co-determined, since not every adopted failure must mean a foregone hit, and vice versa. To inspect the joint effect of firms' *experience* with omission and commission errors, we also use a composite measure of experience, setting failures in proportion to preemptions.

Innovation competition (H4) is a straightforward market-level count of local competitors already offering the focal feature that a firm wants to launch. In our sample, this measure ranges from 0 to 16. Its discriminant validity is high: feature-specific competition is independent of market size and only mildly correlated with overall competition levels (see Online Appendix Table B for descriptive statistics).

For (H5), we rate innovation-specific *consumer sophistication* (Goldsmith & Hofacker, 1991) by the extent to which a market's consumer base buys handsets that are at the technological frontier for the focal innovation. Orthogonal to market size, this measure characterizes customers' feature-specific discerningness. In the validation process for the feature classification (Klingebiel & Joseph, 2016), a group of industry executives had collectively identified the most relevant feature preceding the focal one. For example, consumer sophistication relevant for the local launch of an 8 mega-pixel camera feature would be indicated by the local market share of 5 mega-pixel camera phones, the most recent jump in technological advancement in this space. In cases without generational predecessor, the nearest technology matters: consumer sophistication relevant for a putative UMA (calls over Wi-Fi) feature would be indicated by the market share of Wi-Fi phones, of an A2DP (audio over Bluetooth) feature by the share of Bluetooth phones, and so on. The higher the market share of handsets with indicator features, the closer the average consumer is to the relevant technological frontier and, therefore, able to better discern the added utility of focal feature innovations.

When predicting sequencing (H1)–(H3), we control for firm and feature characteristics. These include firm *size*, proxied by total sales, which may affect a firm's ability to stem simultaneous global release schedules. We also track the time since the firm's first mobile phone sales, to get at heterogeneity in experience that comes with *age*. We include *R&D intensity* as an innovation-focus and quality proxy, which may or may not play a role for the confidence with which handset makers approach the global market with their feature innovations. Moreover, we account for variance in financial rollout constraints through *resource momentum*, a ratio of firms' sales performance in relation to how they could have expected to perform. Expectations are longitudinally formed ($\text{expectation}_t = \text{alpha}^*\text{performance}_{t-1} + (1 - \text{alpha})^*\text{expectation}_{t-1}$), and we use an alpha of .3 (alphas between .1 and .8 generate qualitatively comparable results to those we report). Finally, we control for potentially unobserved feature-specific effects by entering feature dummies into all models we run.

When predicting the market of first entry (H4 and H5), we control for market and firm characteristics. The potential mobile-*market size* is approximated through subscription data from the International Telecommunications Union (ITU, 2015). We further include a standard Herfindahl index to reflect *market concentration*, indicating to which extent the market is generally contested or dominated by few firms. We then proxy *market innovativeness* by setting markets' yearly R&D expenditures in relation to GDP, using publicly available data compiled by the UNESCO Institute for Statistics (UIS, 2015). *Market technological standard* is an industry-specific indicator, capturing the penetration of 3G technology. In our data, the share of 3G-enabled handsets among new handsets sold offers a gauge of a markets' position in the industry lifecycle (Giachetti, 2013). At the firm level, we control for local *firm market share* (in addition to including a dummy for whether or not the focal market contains the *firm head-quarter* of the focal firm). Finally, to assess the extent of mutual-forbearance, we include a common measure of *firm multi-market contact* (Yu & Cannella, 2013), counting the number of other country-markets where the focal firm competes against any of the local firms. This captures the degree to which a focal firm's global business is exposed to potential retaliation by local firms.

3.4 | Specification

For Hypotheses (H1)–(H3), we use ordinary least squares (OLS) to estimate the extent to which firm i sequences the rollout of feature innovation j:

$$\begin{aligned}\text{Rollout sequencing}_{ij} = {} & \beta_1\,\text{Novelty}_j + \beta_2\,\text{Failure Experience}_i + \beta_3 \\ & \times \text{Preemption Experience}_i + \beta_4{}'\text{Controls}_i \\ & + \beta_5{}'\text{Feature Dummies} + e_{ij}\end{aligned}$$

Beyond feature fixed effects, we do not account for group structures. Many firms roll out insufficiently frequently to reliably cluster errors e at the firm level, and workarounds do not apply (Cameron, Gelbach, & Miller, 2008; Ibragimov & Müller, 2016). For transparency, we report results with errors clustered at the firm level, as well as firm fixed effects, in Table 2. We report results for dependent variable RS4, with a comparison of results with alternatives documented in Online Appendix Table C.

For (H4) and (H5), we estimate whether or not firm i debuts feature j in market m with a conditional logit specification:

$$\begin{aligned}\text{Debut Market}_{ijm} = {} & \beta_1\,\text{Feature Competitors}_{jm} + \beta_2\,\text{Consumer Sophistication}_{jm} + \beta_3{}' \\ & \times \text{Controls}_m + \beta_4{}'\text{FirmFeature Dummies} + e_{ijm}\end{aligned}$$

The conditional logit estimates the entry probability within each firm-feature set of 13 market observations. This quasi-fixed effects method limits calibrations across firm-feature groups (Cameron & Trivedi, 2005; McFadden, 1973).

Most of our measures vary on a monthly basis. In the standard specifications, we employ a 1-month lag. The reason for this is that rollout decisions, unlike development decisions, are relatively immediate (Klingebiel & Esser, 2020). In supplementary robustness checks, we replicate the main results with a 3-month lag.

4 | RESULTS

4.1 | Effects consistent with the deliberate creation of learning opportunities

4.1.1 | Rollout sequencing

Pairwise correlations of variables predicting sequential entry provide some first indications of the predicted relationships (see Online Appendix Table A). Firms' experiences with the two

TABLE 2 Results (H1)–(H3)

	I: Baseline	IIa: Novelty	IIb: Novelty	IIIa: Experience	IIIb: Experience	IV: VCE firm clustered	V: Firm dummies	VI: Excl. home starters
Firm size (logged)	−0.056	−0.071	−0.075	−0.067	**−0.071**	−0.071		−0.037
	(0.01)	(0.00)	(0.00)	(0.01)	**(0.00)**	(0.02)		(0.09)
Firm age	−0.003	−0.003	−0.004	−0.003	**−0.004**	−0.004		−0.022
	(0.73)	(0.68)	(0.61)	(0.67)	**(0.65)**	(0.80)		(0.02)
Firm R&D intensity	−0.015	−0.008	−0.007	−0.012	**−0.009**	−0.009		0.000
	(0.30)	(0.58)	(0.63)	(0.43)	**(0.56)**	(0.73)		(0.98)
Firm resource momentum	−0.003	−0.004	−0.003	−0.004	**−0.004**	−0.004		−0.002
	(0.17)	(0.10)	(0.11)	(0.10)	**(0.10)**	(0.12)		(0.48)
H1: Novelty (months)		−0.014		−0.016	**−0.013**	−0.013	−0.013	−0.007
		(0.00)		(0.00)	**(0.00)**	(0.01)	(0.00)	(0.14)
H1: Novelty (firms)			−0.036					
			(0.00)					
H2: Failure experience				−0.005				
				(0.92)				
H3: Preemptions experience				−0.033				
				(0.03)				
H2/H3: Combined experience					**0.187**	0.187	0.240	0.199
					(0.10)	(0.06)	(0.03)	(0.10)
Feature FEs	Yes	Yes	Yes	Yes	**Yes**	Yes	Yes	Yes
Firm dummies	No	No	No	No	**No**	No	Yes	No
Observations (rollouts)	316	316	316	316	**316**	316	316	191

TABLE 2 (Continued)

	I: Baseline	IIa: Novelty	IIb: Novelty	IIIa: Experience	IIIb: Experience	IV: VCE firm clustered	V: Firm dummies	VI: Excl. home starters
Groups (features)	49	49	49	49	**49**	49	49	48
F	1.83	2.04	2.12	2.06	**2.06**	n.a.	3.61	2.81
R^2	0.27	0.29	0.30	0.30	**0.30**	0.30	0.54	0.52
Adj R^2	0.12	0.15	0.16	0.16	**0.15**	0.15	0.39	0.34

Note: Table contains OLS coefficients (p-values in parentheses) for within-feature effects on the dependent variable of feature-rollout sequencing (logged). Model IIIb in bold font is the main specification whose robustness to alternative operationalizations of the dependent variable is further explored in the online appendix and summarized in Table 1.

types of errors appear to have no strong correlation. All other independent variables also appear to capture sufficiently orthogonal dimensions.

We successively add independent variables into the feature-fixed effect OLS model predicting sequential entry. The baseline Model I shows a negative association between the firm-size control and rollout sequencing, which could mean that big firms are less interested in learning about the commercial fate of individual feature innovations. Yet, it more likely simply reflects that smaller firms find it more difficult to launch everywhere at once, even if they wanted to. This replicates prior findings in the movie industry, where big production budgets were less sensitive to the returns on each dollar spent on international rollouts (Holloway, 2017).

We then examine the influence of novelty (H1), first in terms of months since feature pioneering (Model IIa), and then in terms of number of predecessors (Model IIb). Both go in the expected direction (both with $p <.01$). Respectively, they are responsible for about 12% of the overall variance explained, adding 2% over the baseline model. The more recent the feature innovation, the more likely firms sequence its release. It supports the notion that when proportionately more can still be learned from one market to the next, in order to avoid commercial disappointment, the more likely firms want to capture this benefit.

Model IIIa adds the variables for experience with Type 1 and Type 2 errors. While prior commission errors show little influence on rollout sequencing, omission errors reduce sequencing ($p = .03$). The preemption-experience variable's proportion of variance explained by the model is 8% and r^2 increases almost 2% over the novelty model. It suggests that firms sensitized to competitive preemption more likely roll out simultaneously, which supports Hypothesis (H3). Since it is possible that the balance of past commission and omission errors that determine preference for learning, we include a composite variable of experience in Model IIIb. Its coefficient has a p-value of .09. More launch failures and fewer preemptions increase sequencing, whereas fewer failures and more preemptions decrease sequencing. We rerun the compact Model IIIb with varying DV operationalizations, with a summary of results depicted in Table 1 (more detail in Online Appendix Table C).

4.1.2 | Debut-market choice

We then turn to firms' choice of initial launch market. For this, we select strictly sequential rollouts only, which introduces acceptably little bias in terms of the initial covariates (correlations with the selection dummy are displayed in Online Appendix Table A). We end up selecting the innovation rollouts of slightly smaller firms, on average, but find that our sample also includes market leaders like Samsung that sequenced the rollout of many features.

Descriptive statistics for the set of predictor variables relevant for the debut-market choice estimation (Online Appendix Table B) include relatively high correlation between different measures of competition, the construction of which all share some elements of the focal firm's market position. What shows to be less of a concern is a potential correlation between feature-specific levels of competition and consumer sophistication.

Our baseline control model (Model Ia in Table 3) identifies 60% of entry markets correctly (for comparison: a random model would predict 8% correctly). Firms are more likely to introduce new features into their home market first. This might be because firms' hypothesized interest to test the commercial viability of features in the toughest possible environments, is competing with firms' occasional interest to finalize innovation design in protected environments first, before exposing the innovation to market selection forces. A similar rationale might

TABLE 3 Results (H4) and (H5)

	Ia: Baseline (initial)	Ib: Baseline (parsimonious)	IIa: Learning (unstandardized)	IIb: Learning (standardized)	III: Market dummies	IV: Longer lag
Market concentration	−0.038					
	(.77)					
Market innovativeness	0.097					
	(.68)					
Market technological standard	−0.184					
	(.81)					
Market size (logged)	5.245	4.885	5.637	0.099		5.478
	(.00)	(.00)	(.00)	(.00)		(.00)
Firm headquarter	1.741	1.929	1.831	2.706	0.641	1.951
	(.00)	(.00)	(.00)	(.00)	(.11)	(.00)
Firm market share (logged)	4.634	4.623	5.232	0.216	5.837	4.611
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Firm multimarket contact	−0.047					
	(0.24)					
Learning signal: Feature competitors			0.409	0.156	0.450	0.419
			(.00)	(.00)	(.00)	(.00)
Learning signal: Consumer sophistication			1.463	0.057	1.248	1.443
			(.03)	(.05)	(.09)	(.04)
Firm-feature rollout FEs	Yes	Yes	Yes	Yes	Yes	Yes
Market dummies	No	No	No	No	Yes	No
Observations (markets)	2,431	2,431	2,431	2,431	2,431	2,379

TABLE 3 (Continued)

	Ia: Baseline (initial)	Ib: Baseline (parsimonious)	IIa: Learning (unstandardized)	IIb: Learning (standardized)	III: Market dummies	IV: Longer lag
Groups (sequential rollouts)	187	187	187	187	187	183
Log likelihood	−189.00	−189.93	−174.73	−208.43	−158.25	−173.56
Chi^2	581.30	579.44	609.84	542.43	642.78	591.66
Pseudo R^2	0.61	0.60	0.64	0.57	0.67	0.63

Note: Table contains coefficients (p-values in parentheses) for clogit predictions of the debut market in sequential rollouts. Clogit estimates within firm-feature rollouts.

explain the relationship between market share and debut-market choice, one that is partially correlated with home-territory status. Both might also stand to lower distribution expenses, reducing cost of experimentation.

Addressable consumer-market size additionally influences debut-market choice, which may be driven not as much by an interest in learning as an interest to monetize as widely as possible. Competitive intensity and multi-market contact do not explain substantial amounts of variance. This is in part due to the high correlation with the market share variable—in an unreported model omitting market share, at least the coefficient of intensity becomes negative (overall predictive power is lower). Furthermore, market innovativeness and technological standard seem weakly associated with debut-market choice, underlining that launch decisions are innovation-specific and do not follow a general pattern of always launching in the same markets first. We proceed without these controls, losing little predictive power (Model Ib).

Model IIa, which predicts 68% of entry markets correctly, adds the variables for feature competitors (H4) and consumer sophistication (H5). *p*-values are .01 and .03, respectively, and coefficient signs go in the expected direction (this also holds true when they are entered individually). It suggests that those firms that are likely interested in learning do indeed seek out markets where there feature innovations have to withstand the test against early-moving competitors and discerning consumer choices. Although the conditional logit estimation adjusts for groups (the 13-country choice set for a launch), the coefficients are hard to interpret, because variable levels might differ across groups. To check robustness, we standardized variables (Model IIb) such that within each firm-feature group, variable values are ranked and then given values from 1 to 13. Results remain consistent. We also rerun the analysis with variables lagged by 3 months (Model IV). Results are consistent.

We conducted a number of additional analyses. As noted above, there are multiple ways to operationalize our dependent variable, results for which we compare in Online Appendix Table C. Furthermore, Online Appendix Table D summarizes potential alternative explanations for our results as well as the corresponding robustness checks. In particular, we are able to exclude supply-side constraints, resource momentum, and various market characteristics (Online Appendix Table E) as explanations for our results. We are also able to trace the mechanism more closely by showing a waning concern for learning in the choice of later launch markets (Online Appendix Table F). Finally, we provide some interpretation of the economic significance of our findings.

5 | DISCUSSION

Comparing various alternative specifications, our article offers some first insights into the learning opportunities that firms choose to create or not create with their innovation-rollout strategy. The patterns in the data suggest that organizations are cognizant of the countervailing risks of commercial failure (highest with a sequential rollout) and of competitive preemption (highest with a simultaneous rollout) and often behave according to our predictions. Our findings inform the understanding of both entry timing and organizational learning.

5.1 | Contributions to the entry-timing literature

Our examination of innovation-entry patterns highlights heterogeneity that is important for the study of entry. Prior work has begun to highlight that entry is often endogenous (Chang, Kogut, & Yang, 2016; Fosfuri et al., 2013; Suarez & Lanzolla, 2007) and contingent on other strategic considerations (Klingebiel & Joseph, 2016; Markides & Sosa, 2013). Our findings reveal such contingent considerations, including for example that early entrants are more likely to enter small, trying out test markets before going global, than later entrants.

Insight about the altered rollout trade-off between learning and speed for early movers adds to studies of entry showing how pioneers also hedge their bets in other ways. For example, firms have been found to hedge their R&D risk through broader entry, with early movers launching more innovations than more selective late movers (Klingebiel & Joseph, 2016). We add to this an orthogonal set of considerations by showing how firms deal with rollout risk subsequent to development. Taken the earlier and our study together, one can expect early movers to both launch more innovations and to roll these out more sequentially. Late movers more likely launch fewer innovations and roll them out more simultaneously.

An extension to the entry-timing literature thus is the qualification of firms' entry behavior. Adding to past work revealing that learning occurs more likely during iterative rollouts (Holloway, 2017), we show that firms may deliberately sequence rollout for such learning purposes. Entry, consequently, need not be a singular event but can be deliberately drawn-out process. What might look like an early entry in one part of the world is a late entry when viewed from another.

Therefore, accounting for firms' deliberate strategies in the rollout innovations might change the classification of what counts as an early-mover or follower. Two firms completing an innovation at the same time can end up launching in some markets at very different times, even though the decision to enter (and develop the innovation) was taken in synchrony. The timing of a firm's innovation entry in a particular market can thus indicate both its propensity to invest in uncertain innovation and its propensity to sequentially test the innovation so as to learn about its commercial viability. Distinguishing between the two stands to help the unresolved debate about the conditions under which entry-timing positions confer performance and advantage.

Our study suggests one way to qualify entry-timing that is observed in only a single market, rather than globally. If the market contains competing versions of the innovation, the entry is more likely a true debut. If the market also contains a large share of consumers at the technological frontier for the innovation, it increases confidence in the debut classification. If the market contains neither competing versions of the innovation nor many consumers at the technological frontier, the likelihood of misclassifying a local entry as early is high, as it might in fact have come at the tail end of global sequential entry.

Furthermore, the learning rationale in sequential innovation rollout renders entry patterns at odds with those one would expect from firms trying exploit their innovations in a profit-maximizing fashion (Koçak & Özcan, 2013; Yu & Cannella, 2013). In that latter case, one would expect firms to avoid entering markets with competition, especially when rivals there have reciprocal presence in markets where the focal firm already operates (Fuentelsaz & Gómez, 2006; Gimeno, 1999; Haveman & Nonnemaker, 2000). We show that the opposite is true when firms prioritize initial learning over immediate exploitation.

This insight complements prior studies highlighting explorative motives for entering competitive places (Anand et al., 2009), which tended to focus on considerations of mimetic adoption under innovation uncertainty. While such logic applies predominantly to the initial innovation investment decision, we offer an additional mechanism that generates similar entry patterns, but is driven by rollout-strategy decisions: firms seek out counter-intuitively competitive market environments for testing purposes. Studying entry into competitive market environments reliably, therefore, requires information about the extent to which firms might want to learn from initial trial entries.

5.2 | Contributions to the organizational-learning literature

The entry behavior of the firms we observe indicates an appreciation of when the creation of learning opportunities is advantageous. It thus provides a window into when organizational learning is not an automatic by-product of experience, but the result of a deliberate effort (Huber, 1991). "Deliberate learning is distinct from autonomous learning through cumulative experience in that it results from the planned activities of managers and staff conducted with the explicit intent of acquiring, creating, and implementing new knowledge" (Lapré & Nembhard, 2011, p. 41). While the literature on experiential learning is generally deep, our study fills a gap in the understanding of when firms deliberately create learning opportunities that would not otherwise exist.

The conditions under which firms deliberately prioritize learning over other activities are not well-defined, despite indications that such a choice is consequential for performance in competitive markets (Arthur & Huntley, 2005; Haunschild & Rhee, 2004). Deliberate learning is evident in quality-management functions, prototyping and screening routines, and training modules, for example (Lapré, Mukherjee, & Van Wassenhove, 2000). Such institutionalized activities are often regarded as good management practice but limit the study of learning opportunity-specific decisions. Firms more explicitly consider the costs and benefits of investing in learning when they decide to conduct more research before funding a project (instead of starting the project), carry out due diligence on an acquisition target (instead of implementing the take-over), or offer a short-term contract to an executive (rather than a permanent one), for example, even if these actions carry potential downsides.

While prior work has concentrated on conditions under which one firm learns from another effectively (Baum & Ingram, 1998; Haunschild & Miner, 1997), what type of process (Levinthal & Rerup, 2006; Weick, Sutcliffe, & Obstfeld, 2005), and experience (Greve, 2011; Madsen & Desai, 2010) might influence learning effectiveness, and the performance implications of such learning (Eggers, 2012; Eggers & Song, 2015), we examine when they might deliberately try to do so. A better understanding of what makes firms actively seek out opportunities to learn is novel and provides a much needed look at the activation stage of the organizational learning process (Argote & Miron-Spektor, 2011).

While in the development process for innovations, firms cannot easily avoid learning (McGrath, 2001), our context of postdevelopment rollout offers discretion over whether or not firms want to learn more about their innovations' commercial viability before going all in. It is reassuring that our sample firms indeed appear to sequence more when success is less obvious, namely when innovations are more novel and, therefore, uncertain. That novelty would drive sequencing also speaks to research arguing that firms reduce commitment in the face of uncertainty (Klingebiel & Rammer, 2021; Trigeorgis & Reuer, 2017). In line with an options logic, market-acceptance uncertainty systematically influences the calculus of firms that have a choice over whether or not to learn. Our article directly problematizes concurrent tradeoffs with competitive-preemption uncertainty and shows that with more novel innovations, firms dip their toes in local markets first, with less novel ones, they take the plunge into the global market.

Of course, in our study, we do not preclude the possibility of other types of learning occurring in parallel to innovation rollout. Nor do we suggest that the specific lessons learnt from sequential rollout need be all-informing. Learning may occur in absence of intentional efforts to do so (Argote & Todorova, 2007), and firms may learn the wrong things or operate in an environment so unstable or complex that it renders insights useless (Dahlin, Chuang, & Roulet, 2018). In our case of sequential rollouts, learning is evident in flop features being rolled out to fewer markets than hit features, even if we do not know in detail which kind of inferences firms make (Williams, 2007). What is important is that firms' greater use of sequencing for novel innovations is consistent with an ex-ante appreciation of learning opportunities and not easily explainable in other terms.

Understanding the effects of error-type experience on learning choice also contributes to the organizational learning literature an important distinction in, and a more fine-grained treatment of, experience. While prior work has examined heterogeneity in failure intensity (Kim, Kim, & Miner, 2009), our study recognizes a very common, albeit overlooked dichotomization of specific failure: commission and omission errors. In particular, our study recognizes differences in the impact of experiences with commission and omission errors on decisions and articulates when experience may have null, negative or positive effects on learning motivation.

With firms' learning preference contingent on prior experience with errors of commission and omission, our article also provides a window into how firms might change their decision-making behavior in response to feedback (Gavetti et al., 2012). Insights into such path-dependency complement the analysis of how performance feedback might affect risk taking (Haunschild, Polidoro Jr, & Chandler, 2015; Kacperczyk, Beckman, & Moliterno, 2015) or the propensity to explore versus exploit (Raisch, Birkinshaw, Probst, & Tushman, 2009; Wilden et al., 2018), for example.

Firms in technology settings such as ours cannot easily avoid risk altogether, but rather must choose in which form they want to take on risk: the possibility to fail big or to be preempted (Garud et al., 1997). Learning in sequential rollouts reduces exposure to risk of generating errors of commission while increasing exposure to risk of making errors of omission. Our article highlights that firms' preference for either is shaped by their recent experience. We therefore extend a nascent stream of work examining firms' readiness to countenance the possibility of making commission or omission errors (Csaszar, 2012; Klingebiel, 2018; Puranam, Powell, & Singh, 2006). Firm decision making is sensitive to error-type experience: a history of producing flops increases the motivation to learn through sequencing, whereas a history of missing out on hits decreases it.

Finally, our results suggest that firms deliberately seek out learning opportunities with strong signals of success and failure. Considerations of signal informativeness complements knowledge on firms' preference for low-cost learning opportunities (Bingham & Davis, 2012; Sitkin, 1992). It suggests that learning objectives drive sequencing, consistent with what signal-detection theory would prescribe (Green & Swets, 1966; McNicol, 1972).

For sequencing to be a worthwhile learning strategy, initial launch markets ought to display the characteristics of useful testbeds. Although there are some home-country entries consistent with Greve (2000), we find that for other innovations, firms seek out launch markets that contain a greater number of competitors that already offer the focal innovation. Performing against such innovative competition is a higher bar and can provide more conservative signals of success. Similarly, beginning rollouts in receptive markets where consumers are most ready to make use of an innovation generates conservative signals of failure. Taken together, the debut-market choice patterns we observe suggest firms deliberately create learning opportunities.

DATA AVAILABILITY STATEMENT

Datasets used for this study can be made available through the corresponding author upon reasonable request. Third-party restrictions apply.

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