

ENTRY TIMING AND INNOVATION STRATEGY IN FEATURE PHONES

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Research summary: This inductive study examines how firms make decisions about the timing of innovations, focusing on the mobile handset industry during the feature-phone era. Through qualitative and quantitative data, we reveal how individual technology-entry decisions are influenced by a portfolio-level timing preference, and how this preference informs other aspects of innovation strategy, too. Early movers address greater, more uncertain revenue opportunities with broader, less selective innovation portfolios. Conversely, late movers target lower, more certain revenue opportunities with narrower, more selective portfolios. While timing per se seems unrelated to performance, a timing-strategy alignment is. Future research on the equifinal configurations we propose—broad/nonselective for early movers and narrow/selective for late movers—could thus help resolve the debate about the link between timing and performance.

Managerial summary: We study how firms make decisions about the entry of new product features, in this case mobile phone technologies. During development firms weigh the scale and likelihood of features' commercial success. Some firms display a preference for earlier entry, which offers temporary monopoly rewards if uncertainty resolves favorably, while others tend to opt for later entry, which offers greater certainty but lower rewards due to competitive preemption. The innovation portfolios of these companies thus pursue differently structured opportunities, bringing about different strategic approaches. Since early movers aim for big hits to compensate for a higher failure rate, they launch a broader set of features and exert little selective pressure on the development portfolio. By contrast, late movers' lower payoffs reduce their tolerance for failure, making them launch fewer features and emphasize selectiveness; i.e., they invest in learning from the resolution of uncertainty so as to choose features more discriminately. When we examine innovation performance, timing has no significant effect but matching timing with feature breadth does. Copyright © 2015 John Wiley & Sons, Ltd.

INTRODUCTION

Entry timing is a key concern in competitive strategy, yet little is known about it. Timing influences adoption and diffusion (cf. Hoppe, 2002) and is often used to explain firm performance (cf. Fosfuri,

Lanzolla, and Suarez, 2013). But although entry timing is no longer assumed to be exogenous, few studies shed light on how managers actually make timing decisions.

Our inductive study addresses this gap. Using a hybrid approach (Creswell and Clark, 2011), we combine both qualitative informant concepts and quantitative market data from a carefully controlled context: the mobile handset industry during the feature-phone era in the 2000s. This approach enables us to see how managers make decisions about the timing of new-feature entry, what they consider when making these decisions, and how timing relates to other strategic choices.

Keywords: innovation strategy; entry timing; strategic management under uncertainty; hybrid induction; mixed methods; timing of innovation

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Building theory of entry-timing decision-making is important because central claims about the relationship between entry timing and performance continue to be disputed. The market-entry literature finds positive overall performance effects (cf. VanderWerf and Mahon, 1997), negative effects (e.g., Golder and Tellis, 1993) as well as effects that are confined to specific settings (e.g., Boulding and Christen, 2009). More sophisticated econometric controls for endogeneity can only go so far toward resolving such divergence in findings. It might be more helpful instead to ascertain under which conditions practitioners expect to realize performance benefits as a result of their timing choices.

We explore firms' timing decision making in the context of feature entry, which may involve less investment than market-entry decisions but faces similar constraints: firms have to reconcile commercial uncertainty with the threat of possible competitive preemption (McCardle, 1985). Prior to smartphones, competitive fortunes in the handset industry depended on offering novel features (Giachetti and Lampel, 2010; Koski and Kretschmer, 2010), and opting for the wrong features could easily erode competitiveness (Dediu, 2012).

Our inductive inquiry contributes in two ways. First, we provide an account of the deliberate decision making that can explain systematic strategic differences among firms with different entry timing. Firms' approach to investment uncertainty makes them self-select into moving early or late, and they align other aspects of their innovation strategy accordingly, emphasizing either breadth or selectiveness. The intentional alignment with innovation strategy is a probable source of the unobserved endogeneity in the entry-timing literature.

Second, by uncovering the relationship between entry timing and innovation strategy, our study offers a better understanding of the process by which both early and late movers may achieve high performance. The possibility of such performance equifinality offers an explanation for the divergent findings in prior studies and underlines the need for a contingency view of entry timing's performance advantages.

ENTRY TIMING THROUGH A PORTFOLIO LENS

When to launch an innovation is a central question for organizational strategists. Correspondingly,

researchers have attempted to ascertain the advantages fast movers accrue over slow movers. Multiple mechanisms have been proposed that could work in favor of particular timing positions, but verification of performance effects has proved challenging (for exhaustive overviews, see Fosfuri *et al.*, 2013; Geroski, 1995; Kalyanaram, Robinson, and Urban, 1995; Lieberman and Montgomery, 1988, 1998, 2013; Suarez and Lanzolla, 2007; VanderWerf and Mahon, 1997).

Ambiguity in empirical findings is partly due to the difficulty in bounding the phenomenon. Most timing studies have focused on entry into new product markets (e.g., Klepper, 1996). New market emergence is a rare occurrence, however, and context parameters often too unique to allow for meaningful comparisons across different new markets (Lieberman and Montgomery, 2013). Moreover, the increasing dynamism of many industries makes persistent timing advantages hard to detect (Suarez and Lanzolla, 2007).

Perhaps even more importantly, timing is not exogenous. Therefore, it is difficult to relate timing to performance directly. In fact, managers might deliberately decide when entry is most advantageous to the firm. There is indication, for example, that entry speed varies with the proximity of a firm's capability base's to the new product market (Lee, 2008) and the types of products typically offered by the firm (Robinson and Chiang, 2002). Such variation is likely due to deliberate decision making, with managers determining whether early or late entry is more advantageous to their firm's idiosyncratic situation. Instead of trying to ascertain an elusive timing-performance relationship, a more fruitful avenue for inquiry might thus be the conditions under which a particular entry-timing position is expected to provide performance advantages.

However, little is known yet about the aspects managers consider when they make timing decisions. Building theory here is particularly important, given that firms decide on more than just the occasional new-market entry. They also time the introduction of new products to existing markets (Ethiraj and Zhu, 2008), product generations (Franco *et al.*, 2009), new product niches (Greve, 2000), and new product features (Paulson Gjerde, Slotnick, and Sobel, 2002). All of these decisions share a tension between uncertainty about commercial success and competitive preemption

(Agarwal and Bayus, 2004), and, in the case of new technology or feature introductions, occur frequently (Giachetti and Marchi, 2010).

Recurrent instances of timing decisions are not only easier to compare and study effectively; e.g., the repeated nature of feature-entry decisions, for instance, also makes it likely that firms pursue overarching strategies that apply to multiple successive entries. This points to the usefulness of adopting a portfolio lens when exploring timing decision making. Beyond decision-specific considerations, managers might pay attention to overarching portfolio-level considerations when determining the timing of individual entries.

Here, the nascent literature on the strategic management of new product portfolios could offer meaningful parallels. Recent work illuminates how firms alter their portfolios based on industry conditions (Putsis and Bayus, 2001) or firm capabilities (De Figueiredo and Kyle, 2006). Often, firms deliberately aim to structure their portfolios to capitalize on distinctive strengths (Sarangee and Echambadi, 2014; Shankar, 2006).

Especially salient for our study is the notion that firms differ in how they allocate resources across new product propositions to capture unclear market opportunities (Eggers, 2012; Wernerfelt and Karnani, 1987), and correspondingly in the effort they undertake to discern *ex ante* the commercial viability of new product propositions (Danneels and Kleinschmidt, 2001; Klingebiel and Adner, 2015). Such variation in portfolio approaches is likely influenced by the uncertainty of product success (Klingebiel and Rammer, 2014; Sorenson, 2000) and the propensity of competitors to gain footholds in new product categories (Giachetti and Dagnino, 2013; Sorenson *et al.*, 2006).

Both of these are concerns for timing decisions too, so it seems judicious to investigate the extent to which firms coordinate timing and portfolio aspects of their strategy. Therefore, we make new product portfolio considerations a central focus in our quest to uncover the managerial rationales underlying timing decision making. Interplay between timing and portfolio considerations could provide explanations for conflicting findings on the relationship between entry timing and performance. Our paper examines this interplay, uncovering managers' strategic rationale for feature-entry timing decisions.

METHODS

Research design

Although the literature has a rich empirical tradition centered on the performance implications of early market entry, little is known about how entry-timing decisions are actually made (Fosfuri *et al.*, 2013; Lieberman and Montgomery, 1988, 1998; Suarez and Lanzolla, 2007). This calls for a grounded inquiry, relying on field informants (Eisenhardt and Graebner, 2007; Yin, 1994). Unfortunately, although it is possible to ask managers how they make decisions about the timing of entry, it is more difficult to observe the actual decisions. This difficulty is compounded by the recurrent nature of innovations. Related research has been able to detail individual entry decisions (Burgelman, 1983; Geroski and Vlassopoulos, 1991), but observing multiple, irregular occurrences of the phenomenon would have required multiyear site access. Tightly linked quantitative data makes this easier.

Therefore, we chose not only to conduct interviews with managers at handset manufacturing firms, but also to seek quantitative information from secondary sources about their firms' feature entries. The combination addresses the respective limitations of each method, allowing us to observe timing decisions as well as the managerial rationale behind them. By giving equal importance to qualitative and quantitative data, our paper goes beyond the hybrid research designs adopted in other studies (Edmondson, 1999; Fauchart and Von Hippel, 2008; Guler, 2007; Klingebiel and De Meyer, 2013).

Our objective is to build theory and our hybrid approach, consequently, is inductive. Instead of providing formal tests, we complement qualitative analysis of the phenomenon with quantitative corroboration of emerging insights. This enables us to propose theoretical relationships that are both argumentatively plausible and statistically likely (Creswell and Clark, 2011). Compared to inductive methods relying on qualitative data alone, a hybrid approach increases confidence in explanations of phenomena relative to alternative interpretations (Edmondson and McManus, 2007; Jick, 1979).

Our collection of qualitative and quantitative data proceeded in parallel and informed each other. As detailed below, we acquired an initial batch of quantitative data to identify the population of companies, a subset of which we then contacted

for interview. As concepts emerged from qualitative analysis, we collected further quantitative data and also went back to interviewees for clarification and contextualization. Informants also helped us triangulate our coding of quantitative variables.

Empirical setting

Our research context is the mobile device industry. The industry is one of rapid technological obsolescence and fluid competitive dynamics, where performance advantages from innovation are short-lived. This is especially true for the feature-phone era in the 2000s. By this time, mobile devices had reached quality levels for voice call transmission beyond which consumers were unable to discern differences between devices. In response, handset manufacturers differentiated new product offerings through added functionality, equipping products with ever more technological features not hitherto part of telephony devices (Giachetti, 2013). Therefore, feature innovation was a particularly salient characteristic of competition during this period.

The feature-phone principle of competition was well established by about 2001, whereas by 2010 the move toward so-called smartphones intensified. By then, there was a dominant design and manufacturers started to differentiate through computing power, software integration, and “apps,” rather than through added features. Our 2004–2008 observation window thus provides a timeframe during which the rules of the game remained largely unchanged. This is an important, albeit often ignored, control parameter for the reliable estimation of performance effects related to the entry timing (Lieberman and Montgomery, 1998).

For the empirical study of the entry timing, the mobile handset industry during the feature-phone era is also a fortunate choice of setting because the base patents for new technologies were frequently held further upstream by suppliers or by industry standard consortia. Handset makers were often technology takers (Paulson Gjerde *et al.*, 2002: 1269), with their patent positions referring more to integration solutions than underlying technologies (Giachetti and Marchi, 2010). Their principal mode for adding value was to integrate a new feature such as, for example, Wi-Fi into mobile devices. As a result, one manufacturer’s patents did not prevent other manufacturers from developing their own integration solutions (in the smartphone

era, by contrast, legal barriers have increased). This levels the empirical context for the study of entry timing.

Our setting is also bound in space. Confining the analysis to a single market, Germany, allows us to trace more confidently the effect of timing. It eliminates concerns arising from aggregate measures that disguise heterogeneity across countries. Although handset manufacturers are global players, they tended to develop distinct marketing strategies for each major regions (i.e., the Americas, Europe, and Japan/South Korea), due to different mobile network standards and varying consumer preferences (Walkley and Ramsay, 2011). As confirmed by both interviews and quantitative data, Germany is among the countries within Europe where feature-phone products were launched first. This minimizes the potential problem of firms’ entry behavior being contingent on market experiences outside the scope of our observations.

Within the boundaries of our empirical setting, we are able to identify all competing firms. Forty six handset manufacturers introduced to the German market at least one new phone during 2004–2008. This includes all firms that developed and designed handsets, without necessarily assembling them. Where phones were rebranded by network operators or sold under different labels, we identified the company that had originally developed the phone. Overall, the German market saw 838 product launches during 2004–2008. Via these phones, 69 unique feature innovations were introduced to the market, with each firm launching a different subset of features. There were a total of 393 firm-feature entries during 2004–2008.

Qualitative data

Our qualitative data comprises interviews with 68 individuals at 12 handset manufacturers. We first established the overall population of handset makers, using the quantitative sources described below, and then approached the biggest seven firms for interview. Subsequently, we approached five smaller players, irrespective of rank order. The aim was to generate a sample rich in dimensions of size (large and small), headquarter location (Germany as well as abroad), home market maturity (Western as well as Asian), incumbency (young and old), performance (high/low), and entry timing (early and late movers, to the extent to which this could be discerned at the outset). Conducting such

theoretical sampling allows us to check emerging constructs' robustness across different contexts (Eisenhardt, 1989; Tracy, 2010).

Most interviews were conducted in 2007 and early 2008, the height of the feature-phone era, before today's smartphones started to emerge. Our first point of contact was usually the top-management team member responsible for innovation. Interviews would then cascade to lower tiers, including the heads of new product development portfolios, innovation, and/or marketing, as well as several functional specialists. The majority of interviewees had been with their employer for more than five years, with at least two years in their position of expertise. All had substantial exposure to their firms' innovation decision making.

Each interview followed a semi-structured questionnaire guideline with a set of prompts. To solicit narratives of decision making about the timing of feature innovation, we would first ask for descriptions of the process that ultimately led innovations to appear on the market. Following on from this, rather than asking for a complete and systematic report of all features ever launched by the firm, we probed for detailed accounts of selected timing decisions. If respondents did not identify features themselves, we would ask how their firm decided whether or not to launch X (choosing from a list of features we had already managed to catalogue). In the later stages of data collection and analysis, we also placed emphasis on the clarification and corroboration of emerging constructs.

Interviews typically lasted between 45 and 120 minutes, totaling more than 100 hours. In order to tape and transcribe interviews, we signed nondisclosure agreements with all parties. We are, therefore, not permitted in this paper to attribute quotations to individuals or companies.

Beyond interviews, we developed on-going relationships with a subset of firms. These enabled us to contact a number of senior practitioners repeatedly to verify our coding of constructs. In addition, two companies provided access to internal documents and meetings. Select live observations at such meetings, where we saw decision-making unfold, increased both our understanding of the subject matter and our confidence in the inferences we drew from reported data.

Our analysis of the interview narratives followed the accepted sequence of open, axial, and selective coding (Corbin and Strauss, 2008). This meant that we began by identifying an initial set of salient

concepts, particularly those relating to how managers approach timing decisions, what aspects they take into account in order to make these, and how they deal with decision trade-offs. Few theoretical priors influenced this initial phase. Instead, we aimed to give voice to informants and to identify pervasive constructs, patterns, and relationships (Miles and Huberman, 1994). We then proceeded by probing for the context conditions that gave rise to particular phenomena, exploring connections between emerging concepts. Since data collection and analysis progressed in parallel, we were able to ask interviewees questions that allowed us to corroborate our coding. We concluded by validating core concepts and systematically relating them to each other to form our data structure (Gioia, Corley, and Hamilton, 2012; Saini and Shlonsky, 2012). By this time, we were increasingly cycling between emergent concepts and the relevant literature, to identify precedents and to gauge the extent to which we were discovering new relationships. To provide a sense of our data structure, Figure 1 depicts indicative informant phrases and the associated higher-order concepts most central to this paper.

Note that we derive and uncover potential causal relationships from interview data by examining how respondents argumentatively connect constructs. For example, informants tended to discuss entry timing jointly with uncertainty. The resulting propositions for theory development are presented in the results section of the paper. Note, however, that the nature of our interview data makes it difficult for us to use code frequencies or rankings as reliable indicators of the strength of proposed relationships. The practice is *de rigueur* in differently structured qualitative-only research endeavors (cf. Eisenhardt and Graebner, 2007) but less appropriate for our study because selected informants only gave subjective and retrospective views on their companies and particular decisions (cf. Shah and Corley, 2006). To examine the match between what informants said and what they actually did, we instead turn to our quantitative data, which allows us to provide better support for the general applicability of our propositions.

Quantitative data

Our objective here was to build an exhaustive and highly granular database of the industry, which we could use to identify firms and their

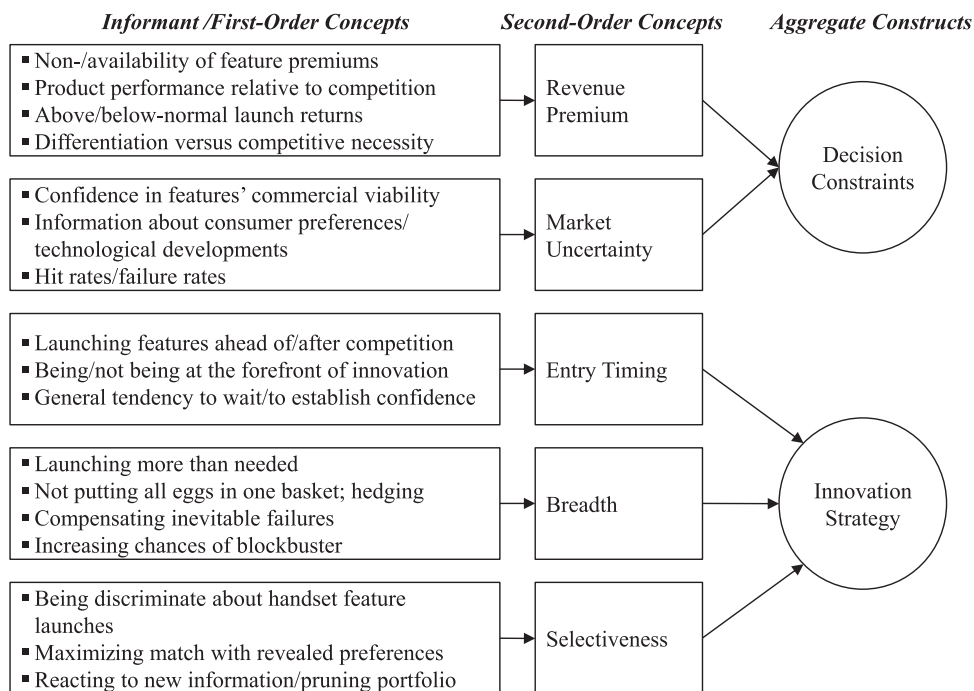


Figure 1. Qualitative data structure

innovation behavior, as expressed in product introductions, and to which we could then relate emerging insights from the qualitative analysis. Currently, two market research organizations provide monthly device-level data in the mobile telecommunications sector: Informa and GfK. They use different methodologies and we acquired both to double-check reliability. Eventually, we settled on GfK as the core of our quantitative data collection effort (see Appendix S1 for detail on the sample data). The GfK data contain information on handset sales units, price, retailer penetration, and selected feature dimensions.

Building on the GfK data, we set out to verify and expand significantly the list of variables relating to handset features. This list was built iteratively, starting with GfK and Informa before moving to consumer advice websites such as GSMarena.com, PDADB.net, PhoneArena.com, Handy-MC.de, and Inside-Handy.de, which enumerate consumer-relevant technological dimensions of mobile phones. We then revisited the list of features with the help of selected company executives whom we had contacted for interviews (more detail in Appendix S2). Having established a final list of 69 features, we were assisted by eight research students who collected the relevant

information for each phone, triangulating between GfK, Informa, and specialist websites.

The construction of our dataset was an iterative and recursive process. We acquired an initial batch of GfK and other data in 2007. We used this to identify handset makers and approach them for interviews. As the first qualitative insights emerged in 2008, we acquired more GfK data and pretested some of the suggested operationalizations. By 2009, we had finalized our specification and were able to define the particular data parameters required. We thus acquired the final GfK dataset, covering 2004–2009 (we use the additional year, 2009, to examine performance of innovations introduced in 2008). In complimentary fashion, qualitative insights iteratively informed the additional collection of web-based data.

The context for timing decision making in the handset industry

The decision locus

Within each of the firms we studied, commitment to entry occurred during new product development. There, the typical problem was less one of ideas than of choice, with a wide array of feature technology options visible to industry participants.

The main challenge was to make the most of limited available information to allocate innovation resources to those features that would generate the greatest returns. Internal uncertainty, mostly relating to the integration of feature technology into handsets, was less prevalent and had been reduced already by prescreening in firms' research functions.

New product development projects tended to be organized around particular handsets, or around a set of minor variants of the same handsets. Handsets, however, are not useful units of analysis for entry timing, as a decision would be about the underlying technology that constituted the defining feature of a set of new handset projects. For example, an interviewed firm conducted three different projects to develop a clamshell handset, a slider handset, and a slider derivative tailored to an operator's request for a particular camera, respectively. These projects shared a common feature in that each handset could hold two sim-cards, an innovation to the new product portfolio of the firm at the time. They were all started concurrently and, when the firm eventually made the unusual decision to abort the launch of dual-sim phones, it froze all three projects simultaneously. Features are thus a more adequate unit of analysis for entry timing in our context than individual handsets. Representing a wider consensus in our sample, one head of new product development said: "Mobiles don't mean much [...] we make one for every customer segment [...] features are the big decisions [...] that's innovation". His counterpart at a competitor similarly commented: "Beyond branding and form factor [...] look what people want; what makes them buy new phones [...] a new feature [that] differentiates the phone." For illustration, another stated that, in 2007, his company launched 28 mobile phones, which were based on six new features. Overall, our quantitative data revealed 69 features launched during 2004–2008 (see Appendix S2 for detail). From the set of 69 possible new features, our sample firms launched varying subsets.

The decision time

During 2004–2008, handset manufacturers faced new product development periods of 12–18 months, on average, if new features were part of the project. As projects cleared decision gates and neared completion, they were hardly ever held back deliberately in order to manage entry

timing. The following statement by a senior innovation manager illustrates this, using the example of a new handset screen technology: "we can't hold back the OLED guys [...] if it works, and they're ready, they're ready [...] we can't just tell the guys to put their phones away for a few months, take a holiday, and launch when we see fit [...] we made a commitment quite some time ago." These commitments were substantial. By the time phones with new features were fully developed and ready for mass commercialization, handset makers would have concluded contracts for the delivery of input materials, signed agreements with operators and retailers, and configured production capacity. Delaying entry at this stage would be costly. Therefore, when managers decided to invest in the development of new features and associated projects, they also made implicit decisions about entry timing.

The decision to follow a pioneer was informed by competitor pipelines, trial reactions from focus groups or opinion leaders, and conversations with carriers and technology suppliers, which provided ample information that could trigger the development of particular features even before competitors' sales became observable. Although handset design details might remain secret till launch, firms could typically gauge whether their peers pursued particular technologies and could form, over time, a gradually more accurate impression of how successful this would promise to be. This is born out in our quantitative sample, with 73 of the 393 firm-feature launches occurring between 3 and 12 months after first introduction by feature pioneers. Bearing in mind that interviewees estimated the time it takes to develop innovative handsets to range between 12 and 18 months, it corroborates that follower firms had often decided to follow pioneering firms before these began to sell devices with the new feature.

Uncertainty versus preemption

Our informants frequently stressed the central tension between commercial uncertainty and the threat of competitive preemption. Only a fraction of feature innovations were successful. Those that were generated so-called feature premiums (interviewees referred to these when phones with a particular feature commanded a substantially higher price, or generated greater sales at the same price, than otherwise comparable phones without the feature). Such outsized returns were available only during the

first few months of a successful feature's lifecycle, before dropping to more normal levels as more competitors started offering the feature.

While access to potential premiums declined over time, confidence in features' commercial viability increased. A manager at a firm with a reputation as a fast mover underlined the high initial uncertainty: "Of course, we don't always know [although] we have a lot of smart people, scouting the market [...] remember i-mode, MMS, TV? Painful, a lot of effort down the drain." His opposite number at a firm considered at the time to be more cautious said: "The longer we wait, the easier it is for us to gauge success. [For example] could we make money off video calling? Was it time? Operators were ambivalent, and [customer focus groups] not all that keen. Ergo, we kept monitoring forecasts while Samsung, Sony Ericsson, and a few others tried their luck at development. And the picture became clearer."

To examine quantitatively the premium uncertainty trade-off in entry decisions, we traced the evolution of feature premiums (the difference between average revenues from phones with the focal feature and revenues from otherwise comparable phones without the focal feature—see Appendix S3 for more detail) on a monthly basis. The magnitude of premiums differed drastically. Many features rendered lackluster returns; merely 13 out of 50 new features pioneered in 2004–2008 generated peak premiums in excess of €2 m a month (the industry benchmark for a feature to be considered a commercial success).

To provide an aggregate sense of the diminishing access to hit-feature premiums over time, we set the average number of firms introducing these successful features in relation to the average erosion of revenue premiums attainable from them. We were able to trace the monthly premiums of 10 hit features for a full 36-month lifecycle; i.e., for hit features launched during 2004–2006. For these, outsized hit-feature premiums were attainable for only about a year after their pioneering entry, by which time, on average, about three more firms had joined the pioneer. These few firms reaped the majority of the rewards to innovation. Within two years of the pioneering entry, on average another four firms had joined, reaping increasingly smaller premiums. During the third year after the pioneering entry, a further five firms joined. By then returns had reverted back to normal levels.

We then went on to examine to what extent the greater availability of information increases

decision makers' ability to select the correct features for entry. To do this, we set feature entry delays in relation to the likelihood of the feature being a hit. The two measures correlate at the 0.01 percent level. A logistic regression of the 345 delay values on the hit likelihood ($p < 0.001$; $\text{Chi}^2 = 19.6$) suggests that each month's delay in feature entry adds approximately one percent to the likelihood of the launched feature being a hit. We repeated this analysis with an alternative measure of success; i.e., whether a feature became a permanent component of subsequent phones. Results were consistent.

Findings

Early and late movers follow different investment strategies

Our observations reveal that firms express their timing preference across multiple entry decisions. Some repeatedly move earlier, targeting higher-uncertainty/higher-premium feature opportunities, while others prefer to move later, targeting lower-uncertainty/lower-premium ones. For example, one firm's executive relayed: "USB ports, cameras, GPS, you name it [...] we waited till we had a clue [about competitors' actions] [...] it doesn't mean we aren't out early sometimes, but overall, I'd say we'd generally give it a year or so before following." Another stated: "[our firm] now tries to be an innovator [...] we were first or second on several [features] last year [...] since the re-org, we have emphasized speed [and risk-taking]", which also illustrates how planning to be an early mover involved a greater readiness to place bets when conclusive information was not yet available. A third commented on how firms' innovation strategy might evolve over the years, with their timing preference evolving accordingly: "Some [firms] try to be ahead of the curve, others are more cautious [with feature launches] and some outright timid [...] and things don't always stay that way [...] we've seen some remarkable transitions, from [serial] leader to follower and back."

For illustration, consider the feature entry behavior of the sample firm Sony Ericsson. The company launched 31 features between 2004 and 2008. Each individual feature launch occurred with varying delay after the respective pioneering entry. Therefore, single-feature delay observations provide an unreliable indication of whether Sony Ericsson should be classified as an early or late

mover. Single-feature decisions are often driven by idiosyncratic considerations. A more aggregated view at the portfolio level, however, reveals tendencies in Sony Ericsson's entry-timing preferences. While, from mid-2005, Sony Ericsson dropped from moving early to moving on average more than a year behind the pioneers, it returned to making more early-mover decisions from 2007. These observed shifts are nonrandom in that they are consistent with what interviewees from the product portfolio team at the firm told us about the evolution of their timing strategy.

Both qualitative and quantitative data suggest firms deliberately self-select into a timing position. Individual feature entry-timing decisions are influenced by an overarching portfolio-level policy. An early-entry preference indicates an investment strategy aiming to generate occasional hits with large premiums, accepting frequent failure. A late-entry preference, on the other hand, indicates a strategy to generate fewer failures, accepting lower premiums. Both strategies can be attractive but operate under different constraints. This is expressed in our baseline proposition:

Baseline: Firms with different entry-timing positions deliberately follow different investment strategies: early movers aim for larger, more uncertain returns, while late movers aim for smaller, more certain returns.

The differently structured investment opportunities at opposing ends of the timing spectrum suggest that early and late movers may maximize their innovation performance through different means. Such conscious alignment is central to the next part of our analysis.

Firms match innovation timing and portfolio breadth

Our interviews indicated that managers at early-mover firms deliberately compensate the commercial uncertainty associated with launching early. For example, one suggested "the last two years we tried to be out there first [...] [development staff] are doing an amazing job [...] we are quite proud of our innovator sheen, [but] all these nonstarter [features], very humbling [...] so we figured we just have to try often enough." The attempt to increase launch breadth when moving

early was seconded by most early movers we interviewed, providing statements like "look, all eggs in one basket, that's suicide in our position [...] we like to hedge the risks we take with electronic paper displays and the like", and "if you strike it lucky, and we did with USB, it sustains ten failures [...] so we keep trying a lot [simultaneously]".

Although it was not always mentioned explicitly, firms appeared to be influenced in their tendency to opt for early entry by their ability to create the broad feature line-up necessary. One executive summed this up in the following statement: "no use trying to make one big splash [...] if you like to move with the fast crowd [...] you have to accept this works only with an innovation engine like [that of a competitor], spouting out stuff all the time [...] that's [also] why you see so many of these [single-feature] upstarts crash and burn." Another development manager surmised that considerations of breadth led his firm to adapt its entry timing policy: "We also learn about our strengths [and weaknesses]. Three big bets [in the last two years] and guess how many disappointments we had [...] not enough [breadth] to make up for the risk [...] now, we prefer to get the few things we manage to do absolutely right [...] so we are not really all that fast."

To assess quantitatively the connection between timing and breadth, we needed to construct measures at the portfolio level. Our sample contains 83 firm portfolio/year observations with at least one new feature (the portfolios of industry entrants are disregarded in their first year). As a portfolio-level timing measure, we used firms' average entry delay in months across the features launched per year. Portfolio breadth refers to the number of features that a firm launched per year. For example, in 2004, Sony Ericsson's portfolio contained 10 new features (breadth), with entry occurring on average 12.2 months after pioneer entry (entry timing). In addition, we constructed a size-adjusted version of breadth, accounting for the fact that big players are more likely to churn out more features than their smaller peers. This version of breadth refers to the number of features launched in proportion to a firm's previous year's total world sales (logged). The operationalization of our normalized breadth measure follows Klingebiel and Rammer (2014).

Table 1 depicts how firm portfolio characteristics vary in accordance with the average timing of innovation. We split observations into timing tertiles: the first group includes early movers with average portfolio delays of 4–13.75 months, the

Table 1. Feature portfolio characteristics

		Proposition 2a		Proposition 2b		Alternative explanations		
		Breadth mean	Breadth/ ln(firm size _{t-1}) mean	Hit rate mean (s.d.)	Perm. rate mean (s.d.)	ln(R&D intensity _{t-1}) mean	Market orientation mean	Price point mean
Entry timing (delay, portfolio averages)	Fastest third: (4–13.75 months) ---33%ile---	5.30	3.29	0.34 (0.28)	0.60 (0.26)	6.58	0.11	260
	Middle third: (13.83–23 months) ---66%ile---	4.18	3.28	0.45 (0.29)	0.72 (0.35)	6.38	0.12	279
	Slowest third: (23.5–35 months)	2.89	2.82	0.55 (0.38)	0.78 (0.39)	6.56	0.10	246
	Anova <i>F</i>	8.03***	5.99***	3.65**	3.31**	1.62	0.72	1.81
	Correlation with delay	−0.44***	−0.26**	0.24**	0.24**	−0.07	−0.03	0.06

** $p < 0.05$; *** $p < 0.01$; $N = 83$ firm/year observations

middle group delays of 13.83–23 months, and the late-mover group delays of 23.5–35 months. Early movers launch significantly (0.1% level) more features than late movers. In part, this difference in breadth reflects firm size, with large firms being able to launch more features on average. When using a size-normalized breadth measure to inspect such potential bias, the results continue to show a significant decline, even if this appears to be largely driven by the slowest third of firms.

Although not reported here, we repeated the analysis with two subsamples of firms split along the 50th size percentile, respectively, as entry timing itself might also be influenced by size (Schoenecker and Cooper, 1998), though less directly than breadth. Results were consistent with those presented in Table 1. Collectively, these findings lend support to interviewees' suggestions of greater breadth for early movers.

The timing-breadth relationship is robust to alternative explanations

We considered a number of alternative explanations for the timing-breadth nexus. One is that firms with low capabilities in upstream research may be constrained in the frequency and speed of feature launch. This would mean that firms in the narrow-late cluster are mainly those that are less able to generate good project ideas. Our interviews suggest that this is not the case,

however. Respondents confirmed that most firms could access the base technologies underlying each feature, since patents were held not by rivals but by suppliers. In addition, interviewees suggested that research generally consumed fewer resources than development, by an order of magnitude. Therefore, even if a firm's research arm was late in exploring a promising technological avenue, and its development department was keen to proceed, amends could be made relatively easily through a temporary increase in research resources. Conversely, late-mover interviewees frequently stated that delay in the introduction of a feature was due to deliberate shelving of development rather than inability to access key technology inputs.

Our quantitative data offers another indication: there appears to be no significant correlation between firms' R&D intensity and our measures for breadth and timing (see Table 1). It suggests that variation in innovation investment does not affect the timing-breadth nexus. This observation reinforces interview testimonies about the laboriousness of learning and selectiveness: making a late-mover strategy work consumes just as many resources as the nondiscriminate multidevelopment approach of early movers.

From an ecological perspective, a firm's orientation as generalist or specialist might offer a second potential alternative explanation. One might suspect specialists to enter earlier into areas close to their core, through phones with advanced technologies

catering to their niche's user needs, while a generalist might follow only if the new technology shows a propensity to become integrated into mainstream handsets (Greve, 2000; Koski and Kretschmer, 2007; Swaminathan, 2001). However, if anything, this is more likely a conservative bias for the breadth-timing nexus, because early specialists are unlikely to have broad feature lineups. It is thus not surprising that, upon construction of a market orientation variable, reflecting the degree to which firms launched features that were alternatives rather than advancements of existing ones, we do not find a systematic relationship. Variation in this measure fails to explain heterogeneity in entry timing (see Table 1).

Another potential alternative explanation for the difference in breadth across early and late movers is that follower firms are differently motivated than pioneering firms. For example, late followers might place more emphasis on cost efficiency in phone production and thus adopt standardized features only. The insignificant differences in R&D intensity already indicate that this is unlikely, with late movers in our context invested in substantial amounts in innovation, which would be inconsistent with a systematic low-cost focus. A second counter indication is that the difference in the average price of new devices in early- and late-mover portfolios is insignificant (see Table 1). This means that it is high-quality phone makers too who prefer to wait with introducing features until more information about their likely commercial viability comes to light, not just firms that focus on economies of scale.

And the third counter indication is that our practitioner informants reported follower decisions as being motivated by feature returns for at least 36 months after pioneering entry. Decisions much beyond this timeframe might increasingly be motivated by other concerns. An alternative explanation through a low-cost bias would thus be more applicable if our analysis included feature entries that occurred between 5 and 10 years after pioneering launches. In order to avoid such confounding effects, we limited our analysis to the 36-months practitioner consensus from the outset.

Firms match innovation timing and portfolio selectiveness

Those considering themselves late movers tended to emphasize breadth much less than early movers. But not only that, they also highlighted learning

and selectiveness, such as in this statement provided by a portfolio manager: "it's not how much you launch, it's how clever you are picking those [features] that really matters". Interviewees reported that a lot of resources would go into learning, to get an idea about the new product development pipeline of competitors, and, over time, to be able to discern whether it was worthwhile to follow. One self-identified late mover suggested: "When we go for a project, we look at ZNet or Heise. Comments show whether people are ready for that new camera Sharp is developing, or Motorola's GPS [...] at the GSMA [a trade conference], people might give you the inside story [...] and] the longer you wait, the better the Gartner forecasts [...] of course, if you want to lead, that's not available."

The increasingly confident assessment of features' commercial viability that comes with greater investments in learning, allows managers to be more discriminating in terms of which features they launch. In the words of one manager: "Our job is not to be this creative genius innovator, throwing crazy gimmicks at consumers [...] others are usually there before us [...] by the time we get our act together, the dust has settled down [...] we are better off figuring out what works and what doesn't. [...] This is where we spend our money." More so than early movers, interviewees from late-mover firms mentioned that they require managers to validate project business cases extensively, and that decision makers allocating resources apply a strong selective filter, involving greater monitoring and recurrent meetings and discussions. This emphasis on deliberate selectiveness is due to the smaller premiums available, as illustrated in the following quote from a portfolio planner: "LG and Samsung with their barrage of [TV and radio-related features] will have syphoned off most of the returns out there [...] when we join them, we cannot afford to repeat their mistakes." Some even directly suggested that late launches were not an option for firms struggling with such adaptive learning: "we are not like Motorola, dominated by all these engineers, however amazing [...] [they are] not so brilliant at listening to the market [...] [but because] they get their stuff out early, they can afford mishaps [...] later it's unforgivable."

Selectiveness is not, as one might think, the inverse of breadth, although there is bound to be some correlation. Firms can launch narrow but indiscriminate feature portfolios, and they can launch broad lineups with carefully selected

features. Unfortunately, careful choices and narrow lineups cannot easily be told apart in our quantitative data. Inspecting hit rates again, however, is instructive. Table 1 shows the means and standard deviations of the proportion of hit features in firms' feature portfolios, staggered by entry timing group. The portfolios of fast movers contain fewer hits than those of slow movers. The same goes for the share of permanent features. More interesting, though, are the standard deviations. Greater dispersion in the rates with which late-mover firms identify hit features and permanent features could indicate that selectiveness can make a greater difference to these firms. Early movers are limited in their ability to identify the right features, even if they conduct elaborate market research. Uncertainty just cannot be entirely resolved at an early stage. By contrast, firm-specific learning capabilities drive heterogeneity in late-movers' propensity to pick successful features. Differences in the extent to which late movers use the greater availability of information over time might provide a potential explanation for the greater standard deviations. This lends support, on an abstract level, to interviewee suggestions that late movers can benefit more from greater selectiveness than early movers.

In summary, strategy varies with entry timing. Firms are more likely to have a broad new feature portfolio if they move early, and vice versa. And we have qualitative indications that late movers place greater emphasis on selectiveness, and vice versa. In short, firms configure their innovation strategy to align timing, breadth, and selectiveness. The proposition below renders a testable form of this argument:

Proposition 1: Firms generate strategic fit between timing, breadth, and selectiveness. Specifically:

Proposition 1a: Early movers display greater portfolio breadth and lower selectiveness than late movers.

Proposition 1b: Late movers display lower portfolio breadth and higher selectiveness than early movers.

The timing-portfolio alignment matters for performance

As a logical next step in the analysis, we were interested in whether fit between these dimensions

of innovation strategy has implications for performance. Interviewees' reported rationale for firms' self-selection into the strategic configurations of early/broad/nonselective and late/narrow/selective is evidently one of expected portfolio performance. But at least as regards breadth, our quantitative observations show that firms' alignment with entry timing is not perfect (see correlations in Table 1). This offers an opportunity to examine the different performance effect of breadth among early and late movers. We would expect early movers to be more likely to benefit from greater breadth than late movers. Due to the unobservable nature of selectiveness, we are unable to check for differences in its effect.

Our quantitative data allow us to trace closely returns to new product portfolios. Crucially for our analysis, we can study the relationship between the number of features launched within a given year and the revenue generated by handsets launched within that year. Because most handsets deliver the majority of revenues within 12 months, we sum up monthly sales each handset made within 12 months of its launch. To create a portfolio-level measure of performance, we sum up the 12-month revenues of all handsets launched by each firm within a given year. As a robustness check only, we repeated all of our subsequent analyses with an intensity ratio; i.e., new product portfolio revenues relative to preperiod sales. Results remain consistent.

A crude comparison would be to see how the mean values of the new product portfolio performance measure differ across the four quadrants of a timing-breadth 2×2 . This would, however, ignore other important drivers of performance. So as to gauge performance drivers more holistically, we constructed a panel model.

With respect to additional performance drivers, our interviewees consistently mentioned the importance of marketing, evidenced by manufacturers' relationships with mobile operators and retail networks. We thus constructed measures for both, to account for a performance effect in the focal period that might be due to operator relationships and retail penetration achieved in the preceding period.

To gauge the extent to which handset manufacturers have relationships with operators, we consulted the product catalogues of the four main network operators in Germany. For each handset, we added up the market share of all operators that offered the handset on post-paid contracts, using yearly operator market shares from Informa's

World Cellular Information Service. Once we had acquired this data for every handset, we used the average across all phones in a manufacturer's new product portfolio per year to indicate the strength of the manufacturer's relationship with German operators.

In order to estimate manufacturers' relationships with third-party retail outlets, we requested from GfK more information on the retail penetration achieved by each phone. GfK constructs its handset sales database from figures reported by retail outlets. It thus gains insight not only into which outlets sell which phone, but also into the handset retail market shares of each outlet. To assess individual handsets' retail penetration, we added up the market share of all retail outlets that listed the handset. We then used the average of this figure across all phones in a firm's yearly portfolio to create the measure needed for our models. Operator listings and retail network penetration proved to be relatively strongly correlated, which is in line with expectations, given that both reflect device makers' marketing strengths.

Since some retail outlets and operators might do better as a result of stocking the most popular brands, these variables are meaningful only if one controls for device maker size directly. Not to mention that bigger firms have bigger new product portfolio sales. Besides size, we also included R&D intensity as a control variable, using reporting data.

Period dummies are also included in the models; and to capture unobserved time-invariant heterogeneity, such as firms' potential strength in engineering or design, we added fixed effects. This results in a smaller sample of 76 observations (21 different firms), because of the need for at least two consecutive years of observed entries.

Table 2 contains the results of our analysis. Model I shows the control model. Besides size, retail penetration appears to predict performance significantly. Operator listings are not significant, which reflects a high correlation between operator relationships and retail penetration. When dropping the retail penetration variable, operator relationships become more significant instead, and the overall variance explained remains broadly stable. R&D intensity also appears insignificant, possibly because the measure imperfectly maps a firm's overall R&D activities to those projects aimed at the Western European market.

Model II incorporates the average delay with which firms launch features. It proves insignificant, confirming our doubts about entry timing's direct performance influence. As a robustness check, we used a second construct to reflect firms' propensity to move early. This alternative is operationalized by the portfolio share of all features launched within six months of their first occurrence on the market. Following within such a short period indicates firms' readiness to develop and launch features before substantial information about their profitability is available. The results remain consistent (see Model III).

Model IV and V additionally contain feature-portfolio breadth. Its direct performance influence appears to be mildly significant (10% level). More interesting, however, is the influence of breadth among early and late movers. To get an sense of this, we split the sample at the 50th percentile of the entry-timing distribution, and generated a variable that takes on the values of breadth if the observation is within the faster half of the distribution, otherwise 0 (feature breadth_fast), and one that is breadth if the observation is within the slower half, otherwise 0 (feature breadth_slow). Our prior analysis suggests that the levels of breadth are endogenous to entry timing, so the models continue to control for entry timing. From the results of Model VI, it emerges that breadth has a significantly positive effect on the performance of early movers, whereas there is no significant breadth effect among late movers. This continues to hold true when we replicate the variable split using the alternative operationalization of entry timing (Model VII).

Our models suggests that entry timing does not have a simple direct relationship with short-term performance but rather provides the context within which particular portfolio strategies are more or less successful. It is easy to imagine a broad early mover sharing the top-performer position with a selective late mover, both capitalizing on their relative strengths. To that end, our model findings provide partial indication that breadth enhances the performance of early movers. The lack of significance for late movers could indicate that the organizational costs of greater breadth (including that of producing multiple failures) are no longer offset by high-premium feature successes. It may also be that high-performing late movers, rather than just through narrower portfolios, distinguish themselves through adaptive learning, launching

Table 2. Fixed effects regression on new product portfolio sales

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII
Constant	0.856 (26.933)	0.636 (27.237)	4.618 (27.101)	-1.200 (26.388)	2.603 (26.298)	-0.237 (26.038)	-2.750 (25.748)
ln(firm size _{t-1})	0.111 (0.055)**	0.110 (0.055)*	0.112 (0.055)**	0.118 (0.054)**	0.119 (0.053)**	0.131 (0.054)**	0.144 (0.054)**
ln(R&D intensity _{t-1})	0.385 (0.828)	0.394 (0.838)	0.267 (0.833)	0.442 (0.811)	0.321 (0.809)	0.444 (0.800)	0.489 (0.792)
Operator listings _{t-1}	0.015 (0.013)	0.015 (0.013)	0.014 (0.013)	0.019 (0.013)	0.018 (0.012)	0.020 (0.012)	0.025 (0.013)*
Retail penetration _{t-1}	0.061 (0.015)***	0.061 (0.015)***	0.062 (0.015)***	0.061 (0.015)***	0.062 (0.015)***	0.056 (0.015)***	0.061 (0.015)***
Average feature delay (A)		-0.003 (0.015)		-0.004 (0.015)		-0.021 (0.018)	-0.018 (0.016)
Proportion of feature firsts (B)			0.169 (0.156)		0.156 (0.151)		
Feature breadth				0.099 (0.050) *	0.096 (0.049) *		
Feature breadth_fast (A)						0.095 (0.037) **	
Feature breadth_slow (A)						0.102 (0.087)	
Feature breadth_fast (B)							0.118 (0.031)***
Feature breadth_slow (B)							0.115 (0.094)
Period dummies	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.	Incl.
Observations	76	76	76	76	76	76	76
Groups	21	21	21	21	21	21	21
F	5.44	4.80	5.04	5.02	5.22	4.91	5.11
R ²	0.52	0.52	0.53	0.56	0.57	0.58	0.59

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

discerningly pruned portfolios. This suggests an opening for future tests of the nexus between selectiveness, entry timing, and performance. To inform future deductive research, we therefore include selectiveness in the following set of propositions:

Proposition 2: Strategic fit between timing and breadth/selectiveness aids performance. Specifically:

Proposition 2a: Early movers are more likely to benefit from portfolio breadth than late movers.

Proposition 2b: Late movers are more likely to benefit from portfolio selectiveness than early movers.

Limitations and extensions

Our analyses, including the quantitative results, are indicative. We restricted ourselves to detailed analysis of a tightly controlled context. The benefits of

this approach include high granularity and internal validity. For example, we are able to identify the entire population of feature entries and can cleanly identify firms' actions and revenues. Disadvantages, however, include the relatively small number of observations, which prevent us from exploring potential nonlinearities. The very first mover, for example, might benefit more than other early movers (Bohlmann, Golder, and Mitra, 2002).

There remains significant room for future research detailing the dimensions by which early movers differ from late movers. An obvious parameter is selectiveness, which we were not able to quantify here. We also encourage examination of factors that might moderate the relationship between performance and the alignment of timing, breadth, and selectiveness. Finally, further work might fruitfully investigate whether there are conditions under which firms willfully opt for nonalignment, clarifying portfolio decision-making further with regard to entry timing.

DISCUSSION

Through analyses of qualitative and quantitative data, we illuminate how firms deliberately self-select into moving early or late; how they align their timing preference with other dimensions of innovation strategy, notably portfolio breadth and selectiveness; and how performance depends on such alignment rather than timing *per se*. These findings likely extend beyond the immediate context of feature entries and allow us to build theory about the timing of innovation more generally, offering a resolution of the long-standing debate about the relationship between timing and performance. Integrating theories of entry timing and innovation strategy stands to aid this endeavor.

Deliberate self-selection

Our first contribution is a better understanding of how firms deliberately choose timing positions. Aware that innovations often fail and that substantial returns to successful innovations are available for a brief period only, managers make choices about the investment strategy for their innovation program. A preference for early entries implies a strategy aimed at generating a few blockbuster successes, whereas consistent late entries suggest a strategy aimed at generating a greater hit rate with smaller returns. One might say these investment strategies are as different as those of venture capitalists and index funds. Measuring early and late movers by the same yardstick is thus unlikely to do justice to their contrasting situations.

That early and late movers face a trade-off between uncertainty and premiums at the individual-decision level has been implicit in prior entry-timing studies (Mitchell, 1989, 1991). Appreciation of the fact that managers are aware of the trade-off, however, was missing. And insight into how this awareness influences decisions repeatedly and across the portfolio was largely missing too. The entry-timing literature has already come to acknowledge that entry is endogenous, but beyond selected firm characteristics that may influence entry (e.g., Hawk, Pacheco-de-Almeida, and Yeung, 2013; Lee, 2008), decision rationales remained unexplored. Our study addresses this by revealing managers' portfolio reasoning in timing decision making.

Our interviewees also did not expect a performance advantage from an early-mover approach

vis-à-vis a late-mover approach. Both can fail for different reasons: early movers might launch a number of flops and not get another chance (also see Vidal and Mitchell, 2013), whereas late movers might not generate sufficient revenues after monopoly returns have been reaped by their faster-moving competitors. Instead, interviewees emphasized the need for strategies that help to make the most of either timing position.

The presence of such managerial reasoning indicates that studies of entry timing stand to benefit from embracing more of a contingency perspective (e.g., Franco *et al.*, 2009; Markides and Sosa, 2013), acknowledging that firms distributed along the entry-timing spectrum pursue different types of opportunities. Disregarding managers' conscious investment choices leads to misidentification of potential effects of timing and might hold a key to explaining the conflicting results of prior studies (cf. VanderWerf and Mahon, 1997).

Timing-strategy fit

Our focus on innovation portfolio management expands the scope of theory concerning entry timing. The empirical evidence suggests that firms configure their innovation strategy in line with their overall timing preference by means of two mechanisms: breadth and selectiveness. Early movers enter with a broader lineup of new handset features than late movers. As they face natural limitations in the accuracy with which they can predict features' commercial viability, they hedge their bets with a more extensive lineup, even if this comes with greater organizational costs. This also confirms part of an earlier conceptual argument about the flexibility needed for investments in uncertain product areas (Wernerfelt and Karnani, 1987).

The reason for late-movers' narrower portfolios is that breadth is costly as more features also mean more failures (and no outsized returns to offset failures). Their emphasis on selectiveness shows that late movers can gain competitive edge by learning from emerging information and pruning their feature portfolio accordingly. For early movers, there is little scope for selectiveness as much uncertainty is irreducible *ex ante*. They have to wait and see which features work out in the market place, whereas late movers can select out innovations before they reach the market. For late movers, the development process is an experimentation platform; for early

movers, the marketplace plays that role (Klingebiel, 2012; Thomke and Bell, 2001).

The finding that managers match innovation strategy to their relative entry timing position—or more accurately, that managers configure their innovation strategy holistically, one dimension of which concerns entry timing—contributes to a strand of literature more concerned with organizational differences among early and late movers than with the direct performance effect of entry timing (Fuentelsaz, Gomez, and Polo, 2002; Markides and Sosa, 2013; Robinson and Chiang, 2002). This paper thus links studies of innovation portfolio management (e.g., Eggers, 2012; Helfat and Raubitschek, 2000) with those of entry timing (cf. Fosfuri *et al.*, 2013). In so doing, it shows that entry timing is but one of a set of integrated elements of a firm's chosen innovation strategy.

To the classic entry-timing literature, we bring the insight that breadth can serve as a shorter-term hedging mechanism, not just as a longer-term mechanism for factor input preemption (Boulding and Christen, 2009). Similarly, we contribute to the field by depicting the dynamic process of learning and selection, a specialist skill among companies often referred to as followers or imitators (Robinson and Chiang, 2002; Shenkar, 2010).

Our paper also extends a line of research that identifies reasons for firms' self-selection as early or late movers (e.g., Hawk *et al.*, 2013; Mitchell, 1989). Empirical studies of entry timing tend to acknowledge the general presence of endogeneity and employ sophisticated procedures to control statistically for it (cf. Boulding and Christen, 2009), but they most often do not specify, let alone measure, the sources of firms' self-selecting behavior. Variables such as breadth, which can be measured relatively easily, stand to enhance future models of entry timing.

Performance equifinality

We provide a close account of entry-timing performance equifinality. In line with informant testimony, we find the effect of timing on performance to be insignificant. But our paper provides initial indication of a performance effect for the fit between innovation strategy and entry timing. Specifically, early movers appear to benefit significantly from greater breadth whereas late movers see no performance-enhancing effect. The indicative analysis of our restricted sample, of

course, provides no conclusive confirmation, but it suggests that future research on the performance effect of entry timing ought to address the fit between breadth, selectiveness, and timing. This is further underlined by the insignificant direct effect of entry timing in our model, as well as by practitioner statements stressing the equal performance potential of moving early and late.

One of the sources of endogeneity that goes unobserved in standard models of first-mover advantage (Lieberman and Montgomery, 1998; VanderWerf and Mahon, 1997) could thus be firm heterogeneity in terms of portfolio breadth and selectiveness. This may also hold true for the reverse; studies of new product breadth may find that its performance effect hinges upon early entry (e.g., Laursen and Salter, 2006; Leiponen and Helfat, 2010). A recent study supports this conjecture, providing one interprets firms' innovative ambition as the likelihood of moving early (Klingebiel and Rammer, 2014).

In aggregate, our findings underline the usefulness of combining qualitative and quantitative data for the examination of research questions that earlier single-method studies could not address. Our novel methodological approach sheds light on a critical gap in entry-timing theory, showing that timing decisions are nonrandom and deliberate, and revealing managers' strategic rationale for aligning timing with breadth and selectiveness. This increases our overall understanding of how firms reap performance benefits in dynamic markets such as the handset industry: by matching the constraints of moving early with greater breadth, and those of moving late with greater selectiveness.

Implications for research

The handset industry during the feature-phone era is an ideal setting for the exploration of how firms handle the tension between entry-deterring commercial uncertainty and the entry-spurring threat of competitive preemption, but it is not unique in its dynamism. Other electronics and consumer goods industries have long witnessed similar accelerations in competitive pace (Brown and Eisenhardt, 1998; D'Aveni and Gunther, 1994), with frequent launches of new products (Franco *et al.*, 2009). Our findings thus stand to have wider applicability and future research might usefully expand the scope for empirical analysis.

In relation to the conduct of such future research, our paper renders a number of practical suggestions. It highlights the fact that timing is often determined alongside other aspects of firms' new product development decision processes. A firm's commitment to develop a product locks in the timing of launch, but the innovation may transcend individual products. New handsets would not provide a meaningful basis of comparison for our study because many do not actually contain innovative features. This underlines the need for entry-timing studies to identify the source of novelty (Lieberman and Montgomery, 1988), for which many prior studies have presumed consistency across settings.

Furthermore, decisions about timing are not contemporaneous with observable launches. The handset manufacturers in our sample decided whether to pursue the development of a new feature and associated handsets well in advance of market launch, sometimes more than a year before. Early decisions are informed by what firms know about competitors' ongoing development activities before they can observe the performance of products launched on the market. Such anticipatory behavior likely extends beyond the handset sector, especially to industries with significant development lead times. Prior studies have typically treated competitors' launches as the critical information signal (VanderWerf and Mahon, 1997), which may lead to biased inferences about the factors that determine entry timing.

Finally, the portfolio aspect of timing indicates that the literature's prevailing focus on selected introductions is less helpful in identifying a firm's general propensity to enter early or late. In this regard, more abstract, self-reported measures such as those in PIMS (Boulding and Christen, 2009; Robinson and Chiang, 2002) potentially reflect more holistically the portfolio nature of entry timing. To complicate things, portfolio-level preferences may also change over time. Prior literature still treats entry timing mostly as a time-invariant characteristic of firms (cf. Lieberman and Montgomery, 2013). Handset manufacturers' evolving tendencies provide a counterexample.

CONCLUSION

We present qualitative and quantitative data drawn from the mobile handset industry to illuminate how entry-timing decisions are made. Our analyses

reveal that firms choose deliberately, aiming to get innovations either right or fast. Early movers forfeit the opportunity to calibrate their feature innovation portfolio as uncertainty resolves and thus spread their bets on temporary blockbuster returns. Late movers prioritize the correct identification and selection of hits, albeit at the expense of lower average premiums. Firms' entry timing seems not to impact performance per se, but aligning innovation portfolio strategy with timing does, especially as regards breadth and selectiveness.

Naturally, the propositions we put forward need further testing. Future work accounting for the equifinal configurations (early/broad/nonselective and late/narrow/selective) would do justice to the different strategies firms pursue at either end of the timing spectrum. Such research would go some way toward resolving the long-standing debate concerning early-mover advantages and disadvantages. A tighter integration of the theory of entry timing and innovation can only facilitate this endeavor. Time, perhaps, to think about the timing of innovation.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix S1. Quantitative data: choice and trianulation.

Appendix S2. Construction of feature list.

Appendix S3. Feature revenue premiums and hits.