ORGANIZATIONAL STRUCTURE AND PERFORMANCE FEEDBACK:
SITUATED DECISION MAKING AND PERSISTENCE IN PRODUCT PHASE-OUT

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Abstract
This study examines the effects of organizational structure on product phase-out. Using quarterly
product-level data on the top five mobile handset manufacturers for the period 2004–2009, we
analyze how the elevation of phase-out decision to higher levels in the firm—and how the extent
of consultation at that level— influences persistence in phase-out decisions. Results show that
elevation speeds phase-out whereas consultation slows phase-out. However, structure also
moderates the effect of persistence following positive and negative feedback. These results
suggest that elevation can increase the inertia and bias in phase-out decisions but only when the
firm is well above (or well below) aspirations. Our findings suggest also that the bargaining
prevalent in consultative environments facilitates phase-out when performance is below
aspirations, but may induce persistence when above. A broader contribution is to offer a theory
of situated selection according to which organizational structure affects phase-out through
information processing and the way managers attend and respond to performance feedback.

Keywords: organizational structure, performance feedback, persistence, product exit
In high-technology industries, rapid technological change requires that firms actively manage their product portfolio by carefully timing the introduction of new products and the selective removal of old ones (Burgelman, 1984, 1994; Henderson and Stern, 2004). Studies confirm that new product introductions help organizations diversify and reinvent themselves (Schoonhoven, Eisenhardt, and Lyman, 1990) and may also improve chances of survival (Banbury and Mitchell, 1995). No less important, though far less studied, is product phase-out or culling: the internal decision to withdraw a product from the market. The phase-out of older products and resulting turnover of product portfolios helps the producer adapt to changing market and technological conditions, which is a critical factor in the firm’s success and evolution (Sorenson, 2000; Burgelman, 2002; de Figueiredo and Kyle, 2006). The timing of product phase-out affects firm revenues as well as the allocation of resources and managerial attention to products in the portfolio (Henderson and Stern, 2004).

Phase-out decisions may be especially challenging when the firm has been exceptionally successful or unsuccessful. Theories of behavioral persistence demonstrate that organizations tend to persist with actions previously associated with desirable outcomes (Lant, Milliken, and Batra., 1992; Miller and Chen, 1994; Audia, Locke, and Smith, 2000; Guler, 2007), a behavior that tilts the balance toward leaving products on the market too long. Organizations are likely to repeat actions associated with favorable feedback (Cyert and March, 1963; Prahalad and Bettis, 1993; Greve, 1998; Burgelman, 2002) because success creates overconfidence in existing knowledge and thereby limits the search for new alternatives (Levinthal and March, 1993). Owing to this “paradox of success,” organizations often remain committed to old products and neither respond to technological or environmental change nor develop new capabilities (Audia, Locke, and Smith, 2000). Similar behavior may be observed following poor performance.
Although it seems counterintuitive to retain poorly performing products, several studies demonstrate that legacies may persist when organizations struggle to interpret properly—and act on—the feedback from negative performance (Cannon and Edmondson, 2001; Baumard and Starbuck, 2005; Rerup, 2009). Learning from negative feedback may be difficult (Audia and Greve, 2006; Eggers, 2012), which helps explain why a firm may escalate its commitment (Staw, Sandelands, and Dutton, 1981; Guler, 2007) or discount alternatives that, given limited initial information, appear not to be viable (Denrell and March, 2001). For example, Burgelman (1994) found that, despite lagging performance in their memory chip business, Intel executives had difficulty switching their focus from memory to microprocessors; similarly, Guler (2007) demonstrated that venture capital firms are often reluctant to terminate even clearly unsuccessful investments.

Although there is robust support for models of behavioral persistence, this body of work generally assumes that decisions—such as those concerning product life—are handled uniformly throughout the firm. That assumption fails to acknowledge managers as the primary determinants of whether individual strategies and products are eliminated or selectively retained (Burgelman, 1991; Henderson and Stern, 2004), and it reflects the view that performance feedback is invariantly processed regardless of the decision maker’s position within the corporate hierarchy. However, studies grounded in the behavioral theory of the firm indicate that responses to feedback may vary with the subunit in which evaluations of success and failure occur. For example, Gaba and Joseph (2012) examined the unique effects of corporate and business unit performance feedback on new product introductions and found different effects for each. Audia and Sorenson (2001) similarly concluded that different functional areas create and monitor their own unique performance metrics and react differently to their respective feedback. These studies
focus on responses to different feedback within the firm, so they leave open the question of how the same feedback is processed by different organizational structures. The organization’s decision-making structure is therefore a significant omission in studies of behavioral persistence and of performance feedback more generally. We define organizational structure in terms of explicitly mandated formal structure and also in terms of formal and informal interactions among individuals in different functions or units (cf. Gulati, Puranam, and Tushman, 2012).

How does an organization’s decision-making structure affect persistence behavior? To answer this question, we set our study in the mobile device industry and examine, across the largest firms, the problem of product phase-out. Organizational structure may have important implications for persistence in product phase-out within large vertical hierarchies because it shapes not only the efficient processing of information, which affects coordination of activities, but also attention to and perceptions of information (e.g. feedback), which has implications for how firms respond. Structure’s role in information processing is a well-established one, in that the firm’s decision making structure enables the efficient collection, processing and distribution of information to help managers navigate and address demand uncertainty (Tushman and Nadler, 1978). Less observed is how organizational structure affects the attention and responsiveness to performance feedback. Studies have shown that decision making is situated (Lave and Wenger, 1991; Ocasio, 1997; Elsbach, Barr, and Hargadon, 2005), and the organizational structure itself has been shown to affect decision making and performance (Csaszar, 2012; Csaszar and Eggers, 2013) as well as cognition and the development of capabilities (Tripsas and Gavetti, 2000; Gavetti, 2005). Accordingly, the structural location of decision makers may amplify or attenuate the inertial properties of and biases in decision making after success or failure. Little is known about this aspect of structure, so explorations along these lines answer the call of scholars to
reintegrate structure into the behavioral foundations of the Carnegie tradition (Gavetti, Levinthal, and Ocasio, 2007).

In light of this important lacuna, we examine the effects of two key structural factors: the elevation of decisions up the hierarchy, and the extent to which portfolio decisions involve consultation with peers. Our main thesis is that structure affects phase-out through information processing in support of coordination and that, because structure situates each decision maker within a particular subenvironment, it also shapes how managers respond to feedback. We argue that a manager’s response to success and failure—specifically, to performance above and below aspirations—may differ because phase-out decisions involve weighing the effects of lost sales (which result from pulling a product too early) against the effects of “cannibalization” (the process by which a new product gains sales by diverting them from the firm’s existing products). The manager’s appraisal will vary with the change in attention focus that accompanies elevated decision making and the negotiations required under a consultative decision-making regime.

We test our predictions using a unique data set of product sales in the German mobile device industry. This industry is a suitable setting because it is characterized by a high level of product turnover (i.e., older products are quickly replaced by newer ones). Henderson and Stern (2004) observed that, “although eliminating a viable, revenue-producing product seems counterintuitive, it is quite common in high-velocity settings, in which obsolescence occurs quickly” (45). Timely phase-out ensures that older products will not divert managerial attention and resources from new products (Greenstein and Wade, 1998). For handset makers, key performance indicators (e.g., unit sales) are widely shared and are watched closely by industry analysts and investors. The single-industry and single-country context of our study minimizes the risk of unobserved heterogeneity because all handset makers are engaged in similar production
activities. The study’s observations are from a period during which overall portfolio health, rather than “hit phone” status, were firm’s primary performance benchmark.

In addition, the organizational charts of our sample firms are roughly similar. Mobile device firms typically give product managers responsibility for a series of products. For example, at Motorola the mobile devices business was subdivided into units dedicated to different technological standards (e.g. CDMA, GSM, iDEN) and into teams managing various smartphone platforms. In each major firm there is a business unit head as well as several layers between that head and the product managers. The firms in our sample also featured such common functions as research and design, product marketing, and sales. However, the process of making decisions about the product portfolio vary; some firms vest such decisions at the product manager level whereas other firms elevate the decision responsibility upward in the organizational hierarchy.

Our study makes several contributions to the literature. First, we contribute to theories of behavioral persistence by positing a role for organizational structure in product phase-out decisions. For this, we link theories of situated decision making (Ocasio, 1997; Elsbach, Barr, and Hargadon, 2005) and performance feedback (Lant, Milliken, and Batra, 1992; Audia and Sorenson, 2001; Greve, 2003b; Gaba and Joseph, 2012) to develop a theory of situated selection in product phase-out. Our theory suggests that internal selection—that is, selective removal of products from the market—is guided by the locus of decision making (elevation) and local interactions (consultation), which underscores the heterogeneity of selection processes within and between firms. Second, we augment theories of performance feedback by elaborating the role of organizational structure. We demonstrate that actions carried out in response to feedback are also function of the organizational level of decision making and the extent of consultation at that level. More generally, our findings of situated selection offer new insights into how
structural and cognitive drivers interact to shape adaptation, of which product phase-out is but one example.

**ORGANIZATIONAL STRUCTURE AND DECISION MAKING**

For much of the past five decades, research on organizational structure has centered on two critical design choices (Simon, 1962). The first of these choices concerns centralization versus decentralization of decision making within the firm (Egelhoff, 1982; Miller and Droge, 1986). In other words: Should decisions be made at lower or higher levels of the organizational hierarchy? The second design choice concerns the extent to which individual units should function autonomously or rather collaborate in decision making (Lawrence and Lorsch, 1967). These two dimensions are especially salient for large firms, which are generally characterized by a system of subunits and multi-level hierarchies that collectively allocate resources while formulating business policies and strategic plans (Chandler, 1962; Williamson, 1985).

Research that addresses the decision-making implications of organizational structure has traditionally been anchored by information processing theory: the study of how structural choices bear directly on the firm’s capacity to collect, process, and distribute such information as plans, budgets, market conditions, and performance feedback (Tushman and Nadler, 1978: 614; see also Galbraith, 1974). From this perspective, the role of structure is to increase information-processing capacity—both vertically and horizontally—and thereby improve coordination among various organizational functions (Gulati, Lawrence, and Puranam, 2005).

We speak of *vertical* information processing when referring to the elevation of portfolio decisions within the vertical hierarchy. In some firms, formal roles and responsibilities or standard operating procedures may lead to these decisions being pushed up the chain of command through such conduits as cross-level communication channels (Galbraith, 1974;
Joseph and Ocasio, 2012). Elevation may also follow routines and unwritten rules of engagement transmitted through social networks and interactions that are less formal. The logic of this argument is that, whether formalized or not, more efficient information processing leads to better outcomes—especially when the environment is complex and/or changing rapidly (Siggelkow and Rivkin, 2005).

By the term horizontal information processing we reference the degree to which information flows between actors at a given level of the organizational hierarchy. Recall that Lawrence and Lorsch (1967) established both the differentiation and the integration of a firm’s information-processing capacity as critical determinants of performance. We focus here on the integration that occurs through consultation, defined as communication and negotiation between actors—via formal and/or informal interactions—that aims to achieve consensus concerning portfolio decisions. Consultation may occur through various information-processing linkages, including dedicated roles, cross-functional teams, organizational goals, and informal channels (Galbraith, 1974). Such consultation is consequential for both cooperation and coordination with regard to a wide variety of activities (Gulati, Lawrence, and Puranam, 2005).

However, information processing is only one mechanism through which organization structure (here, elevation and consultation) may affect decisions such as product phase-out. Organizational structure may also have an effect through its moderating effect on the attention to, interpretation of, and response to information—in particular, performance feedback. Feedback-based response is the attempt by managers to understand the connections between their actions and the organization’s outcomes, and it involves responding to performance that is compared to a reference point or aspiration level. From this perspective, the role of structure is not to facilitate information-processing capacity so much as to determine whether and how the
firm attends and responds to feedback. A given firm’s organizational structure creates idiosyncratic decision-making contexts within subunits, which leads attention to be focused on certain aspects of feedback information to the exclusion of other aspects (Ocasio, 1997).

In short: responses to performance feedback are not uniform, and the cognitive processes underlying any phase-out decision vary according to whether or not decisions are elevated and whether or not they involve consultation with multiple decision makers. Therefore, if decision-making structure varies across organizations then responses to comparable feedback—and choices concerning phase-out—may well differ from one decision maker to the next. In what follows, we examine both information-processing and feedback-related effects of structure.

**Elevation of phase-out decisions.** The elevation of portfolio-related decisions has several implications for the speed of phase-out. With elevation, decisions are transferred vertically from a product manager to a more senior-level decision maker—for example, a vice-president or the business unit chief. Because elevation naturally vests decisions with a more centralized manager, higher-quality and more diverse knowledge can be brought to bear on phase-out decisions. Centralization helps to facilitate dense internal communication flows and increase firm absorptive capacity (Jansen, Van Den Bosch, and Volberda, 2005). Vertical communication is more efficient than horizontal communication because subunit managers are more willing to share information with centralized decision makers. Such information is less likely to be biased in that competing product teams prefer vertical to horizontal communication (so they can monopolize insights that may advantage them (Alonso, Dessein, and Matouschek, 2008). Better information quality will likely yield faster decisions as senior managers are then no longer required to seek out qualifying information or second opinions or to sort through mixed messages.
Centralization also limits the ability of product managers to assert parochial agendas. Product managers tend to screen out information that does not affect their particular products, technologies, or markets; they naturally focus on the problems, actions, and outcomes that reflect their role within the firm (Henderson and Cockburn, 1994). A product manager is probably not aware of all the resource demands of other product managers and does not know (or care) exactly where resources should be directed, an ignorance that hampers coordination efforts meant to support phase-out. Higher-level managers are not embedded in local information filters Argote and Ingram, 2000); hence they can access and appreciate information concerning the entire portfolio and are therefore better positioned to facilitate phase-out. Because these executives consolidate and adjudicate agendas held by lower-level managers, they are better positioned also to manage the entire range of demands across subunits and thus, once again, can more readily and accurately identify phase-out candidates.

By extension, centralized decision makers may be better able to facilitate knowledge exchange across subunits and hence to prevent phase-out decisions that could have mutually destructive consequences (Siggelkow and Rivkin, 2005). Because phase-out involves adjusting a range of interdependent activities—such as factory schedules, operator road maps, and supply chains—greater access to the complete spectrum of information improves coordination in support of product discontinuation. Overall, the efficiency of information processing improves as decisions are elevated within the organization, which suggests the following hypothesis.

**Hypothesis 1 (H1):** The likelihood of phase-out increases with the elevation of product portfolio decisions.

**Consultation in phase-out decisions.** Consultation has implications both for unity of effort (cooperation) and for unity of action (coordination) in support of phase-out (Lawrence and Lorsch, 1967; Gulati, Lawrence, and Puranam, 2005). Problems of cooperation arise from
conflicts of interest. Under assumptions of opportunism or self-interest, collective agreement may fail to occur because of actions motivated by the private benefits of managers. To deal with these inefficiencies and to motivate managers in a uniform way, organizations often put in place incentives, sanctions, and monitoring mechanisms (Williamson, 1985). They may also rely on more informal mechanisms—in particular, consultation (interactions) between units and managers. Frequent consultation may improve cooperation because it facilitates the creation of trusting relationships and social ties (Gulati 1995; Tsai and Ghoshal, 1998). Interactions create an environment in which a manager can develop a common shared purpose, and they also establish arenas for sharing information and engaging in collective action (Martin and Eisenhardt, 2010; Martin, 2011). Consultation thus facilitates the alignment of interests among managers responsible for different product groups or functions and, at the same time, promotes collectively agreed-upon product life cycles and phase-out dates.

Yet despite the cooperative advantages that result from greater information sharing (Huber, 1991), consulting with colleagues in the context of portfolio management may, on balance, actually slow down phase-out owing to the additional coordination costs that arise from multiple interests. The need for consensus requires that product phase-out decisions be approved by others, which means that diverse and often conflicting demands must be served by any given phase-out decision (Cyert and March, 1963). This negotiation process takes time—and more than that required for the mechanism of H1, whereby decisions are referred up the organizational hierarchy but not necessarily discussed at length. Furthermore, efforts to establish consensus may lead to open disagreement about the means necessary to accomplish objectives or, more fundamentally, may create inconsistency in aims; these effects may complicate or delay decision making (Denis et al., 2011)
For example, product portfolio decisions at Motorola in the mid-2000s involved managers from different functions. Thus portfolio meetings would include representatives from R&D, design, marketing, and production as well as managers handling the relationships with Vodafone, T-Mobile, and other major telecom operators. Decisions to launch or cull products were committee decisions that required a relatively high degree of consensus. On the one hand, this ensured that product decisions were informed by better information; on the other hand, it continually forced managers to revisit and compromise on timing that was appealing to no one but at least acceptable to everyone. The approach was described by one manager as a “redecision-making democracy” that delayed portfolio management decisions of all kinds. So consultation has both advantages and disadvantages. Although it achieves the pooling of necessary information, it may also end up inhibiting action. On balance, we suggest the following hypothesis.

**Hypothesis 2 (H2):** The likelihood of phase-out decreases as the extent of within-level consultation increases.

**Organizational structure and portfolio feedback.** Organizational structure may affect phase-out not only through information processing but also through its effect on how the firm responds to performance feedback information. This is because managerial responses to success and failure may differ with variations in the attention-directing qualities of the organizational structure (Ireland et al., 1987; Milliken and Lant, 1992; Ocasio, 1995). In particular, we argue that the effect of performance feedback on product phase-out varies with both the elevation (up the hierarchy) of portfolio management decisions and the extent of within-level consultation.

Our feedback model is grounded in the behavioral theory of the firm. In this model, boundedly rational decision makers simplify performance evaluations by transforming a continuous measure of performance into a discrete measure of success or failure (March and
Simon, 1958; Cyert and March, 1963; March, 1988). To do so, decision makers evaluate performance—on some key dimension—with respect to an aspiration level, reference point, or goal (Miller and Chen, 1994; Greve, 1998; Audia, Locke, and Smith, 2000; Mezias, Chen, and Murphy, 2002). The difference between performance and aspirations serves as a feedback mechanism, which provides a signal to decision makers regarding whether or not to maintain current activities and/or to adjust aspiration levels (Greve, 2003b). The aspiration level thus serves as the dividing line between perceived success and failure, and a firm’s most recent performance may be the starting point for a revision of phase out decisions. Although the effect of portfolio feedback on product exit has not been a topic of prior studies, the theory suggests that past portfolio performance may affect product persistence owing to biased managerial perceptions concerning the success or failure of the unit’s portfolio performance (Milliken and Lant, 1991).

Successful organizations tend to experience more inertial pressure than do less successful ones because the pressure to remain consistent is naturally much stronger after a period of success than of failure. External stakeholders will likely expect a continuation of activities that have yielded success in the past, so managers are prone to favoring the status quo and thus to extending product life. Success serves as an indicator that the firm’s actions are effective and often leads to the selective retention of activities that contributed to that success (Greve, 1998; Kraatz, 1998; Audia, Locke, and Smith, 2000; Schwab, 2007). Successful performance can make managers “so complacent, so content with the status quo, that they resist change” (Miller and Chen, 1994: 3). Signals of past success may encourage managers to retain existing products longer, even when faced with technological or environmental change or the availability of newer products to replace them (Lant, Milliken, and Batra, 1992).
Forces inducing persistence may also play a role in responses to failure. When performance does not meet aspirations, managers may escalate their commitment to failing products—making decisions that disregard negative feedback about prior resource allocations, that discount the uncertainty of goal attainment, and that result in the inability to break from a current course of action because of the psychological sunk costs associated with doing so (Brockner, 1992). In the short term, firms find it difficult to shift strategies (Hannan and Freeman, 1984) and may decide to refrain from phasing out a product if portfolio performance improvements are believed to be imminent or if disconfirming information is absent.

**Elevation and portfolio feedback.** Elevation may amplify the persistence behavior delaying phase-out that is characteristic of extremely over- or underperforming firms. The reason is that slack-directed behavior (which follows performance above aspirations) and problem-directed behavior (which follows performance below aspirations) may differ along with the level of the firm at which phase-out decisions are made. Evidence from the behavioral theory of the firm suggests at least two reasons for such differences. First, behavior is most strongly motivated in areas that are considered to be important by managers and their key constituents; second, behavior is shaped by managerial biases and the information available to them for decision making (Cyert and March, 1963). A vertical hierarchy allocates the attention of lower and more senior managers to narrower and broader goals, respectively (Ocasio, 1995). As a result, attitudes toward discrepancies between aspirations and current performance—as well as the information available to address these gaps—will vary with the structural position of decision makers.

A high-performing portfolio reflects one or more successful products, which increases the likelihood of the firm cannibalizing its less successful or older products. At the level of product managers, who typically manage one product after another, this concern may manifest as a desire
to accelerate the phase-out of certain products in advance of cannibalization. Yet social, cultural, and economic incentives, which are reinforced by pressures from external constituents, induce senior managers to focus primarily on the aggregate performance of the portfolio; this focus renders them less concerned about the cannibalization of any single product. Investors and analysts prefer continuity of strategies when performance is good (Benner, 2010), and such pressures for consistent performance are greater at higher levels of the corporate hierarchy because senior managers often either deal directly with the investment community or report directly to the C-level managers who do (Kaplan and Minton, 2006; Wiersema and Zhang, 2011). If the current strategy has yielded a successful portfolio, then there is more external and internal support for prolonging the life of products within that portfolio.

Because senior-level managers are more likely to set the overall portfolio strategy, they are more likely to attribute any subsequent success to that strategy. In other words, when such attributions are made by the same managers who designed the portfolio, those managers become even more inclined to believe themselves responsible for its past favorable performance (Milliken and Lant, 1991). Hence they are likely to implement processes that reinforce the current portfolio mix and to be most concerned with the performance dimension that reflects favorably on their actions. Because they are vested with better information and the capacity to share information and deploy resources across the different product units, senior managers can more effectively extend the life of products in response to constituent pressures and in support of the status quo—provided performance is high.

The same constituent pressures for continuity following good performance are also likely to amplify persistence among senior-level managers when portfolio performance falls below aspirations. Investor concerns about poor performance induce managers to behave myopically
(Stein, 1989), which may manifest as an emphasis on short-term performance and the elimination of spending not clearly related to short-term profitability (Cyert and March, 1963: 171). At senior levels, decisions concerning phase-out are coupled with those concerning cuts in discretionary spending (e.g., advertising, travel, training) and human resources (e.g., by laying off consultants or even employees), cuts that are made to increase current earnings and focus product managers on core activities (Bushee, 1998). When performance problems arise and portfolio decisions are elevated, higher-level managers are likely to devote fewer resources to next-generation than to current products in attempting to boost current earnings (Bushee, 1998); lower-level managers are less likely to exhibit this preference (Gaba and Joseph, 2012).

Senior managers may fail to recognize that a prior strategy is obsolete simply because they do not immediately benefit from more adaptive representations of the emerging competitive landscape, which usually originate at lower levels of the firm (Tripsas and Gavetti, 2000). Hence these managers may not grasp fully the changing environment or may fail to seek out the source of performance problems, and these deficiencies foster the persistence of current solutions and products. Thus, when the portfolio is not performing well, less aggressive phase-out behavior is likely when those decisions are made at higher than at lower levels. Consequently, we suggest the following.

Hypothesis 3a (H3a): The elevation of portfolio decisions amplifies the extent to which above-aspiration level portfolio performance decreases the likelihood of phase-out.

Hypothesis 3b (H3b): The elevation of portfolio decisions amplifies the extent to which below-aspiration level portfolio performance decreases the likelihood of phase-out.

Consultation and portfolio feedback. Increased consultation may reduce the likelihood that managers will deviate from the status quo when performance is above aspirations. In consultative environments, the portfolio strategy and product phase-out are determined collectively, with each
function or unit “weighing in” on the decision. This may occur through communication channels such as meetings to review products, planning, or design. As mentioned previously, product groups at Motorola met collectively to discuss portfolio planning, which involved upcoming product introductions and exits in addition to longer-term activities. These meetings included representatives from different product groups and from various functions. When portfolio decisions are made in this manner (i.e., with the goal of achieving consensus), excess resources may help to resolve any potential disagreements about which products should receive further managerial attention. Moreover, decision makers then feel collectively responsible if portfolio performance exceeds aspirations; this leads them to interpret success as validating their collective approach and so to favor extending the life of products in the portfolio.

However, attempting to achieve consensus among multiple interests may accelerate phase-out when performance is below aspirations. Poor performance may deplete resources and fragment interests, values, and beliefs; these consequences will likely intensify internal rivalries and motivate managers to challenge the status quo (Ocasio, 1995; Birkinshaw and Lingblad, 2005). Hence the negotiation process faces less collective resistance to change—here, product phase-out—than it otherwise would. Therefore, decision making is more likely to result in product phase-out than when performance meets aspirations. Related research has shown that, during periods of economic adversity, divergent interests lead to a number of organizational changes; these include the replacement of managers (Ocasio, 1994) and the spawning of interest groups or coalitions that might fragment organizational knowledge (Aldrich, 1999: 118).

Finally, if performance is poor then consultation may mitigate the escalation of commitment to failing products. The divergent opinions that normally abound when consensus is sought via collective decision making may help raise key environmental or technological issues
and thereby update perceptions of the firm’s positioning. Such divergence may also serve to highlight any mis-specified attributions for performance. When performance is poor, external attributions dominate and this reduces the unit’s responses to feedback. However, if portfolio management decisions must be approved by various units and performance is poor, then the beliefs underlying those attributions are more likely to be questioned. These considerations lead to our final hypotheses.

**Hypothesis 4a (H4a):** Increased consultation in portfolio decisions amplifies the extent to which above-aspirations portfolio performance reduces the likelihood of phase-out.

**Hypothesis 4b (H4b):** Increased consultation in portfolio decisions attenuates the extent to which below-aspirations portfolio performance reduces the likelihood of phase-out.

**METHODS**

Our study looks at product exit and organizational structure in the mobile device industry during the period 2004–2009. This is an ideal setting to examine their relation because the industry leaders constitute a relatively stable set and because most mobile devices have a short product life. Since there is no single source that combines device-level information with an adequate description of how phase-out decisions are made, in this study we employ qualitative measures of organizational structure in addition to detailed, device-level quantitative data. These data were obtained from a variety of sources, including public filings, press and literary coverage, internal records, and interviews that concentrate on the five largest participants (in terms of units sold) in the mobile device industry. These companies accounted for nearly two thirds of all mobile devices launched on the German market during the time period of our study; they also were the industry leaders, during this period, in establishing the pace of product turnover and development as well as the major device strategies in the marketplace.
The quantitative data sample covers all mobile devices from our five focal firms that were introduced to the German market after January 2004 and discontinued before December 2009. Since a typical phone lifetime is only 4.3 quarters, this period captures multiple updates of handset manufacturers’ product portfolios during a time that saw significant changes in the industry, including development of 3G (third-generation) data standards. This period is considered the era of feature phones, and is prior to the move toward smartphones. The GfK global retail panel served as our primary source of performance data. This panel is regarded as the industry benchmark in data collection because it gathers retail sales figures at the point of phone sales to consumers rather than from manufacturer surveys. The GfK data are also unique in providing phone-level price and sales information. We supplemented and cross-checked the GfK data set with data from competing providers, such as the World Cellular Information Service, Informs World Cellular Handset Tracker, technical websites such as gsmarena.com, and the Strategy Analytics online database.

As mentioned previously, the mobile phone industry is an ideal setting to examine the effects of performance feedback on new product introductions. First, it is a high-velocity industry characterized by a high rate of new product introductions and technological advances (Eisenhardt, 1989, Keil, McGrath, and Tukiainen, 2009). Second, the major players did not change during the period under study even though their relative performance varied. Third, the critical goals of firms in the industry—for instance, unit sales and replacement pipeline—are widely shared and watched by competitor firms and industry analysts.

To ensure accuracy, a subsample of the data was selected and checked against publicly available data on product availability and features. The GfK revenue figures were also checked against Datamonitor estimates, and the former were found to be in line with the latter. Data were
analyzed by quarter; the result was a total of 1,307 product-quarter observations, comprising 337 product exits across 361 devices within the sample. Firm financial data was acquired through Compustat and quarterly reports. Descriptive statistics and correlations for all predictor variables are given in table 1.

*** Insert Table 1 about here ***

**Dependent Variable**

We explore the effect of different decision-making structures and performance–aspiration gaps on product phase-out or discontinuation. In the mobile device industry, the product life cycle is approximately four quarters; see the histogram presented as figure 1.

*** Insert Figure 1 about here ***

The key event for our analysis is discontinuation of a mobile device. Unfortunately, the precise date of a product line’s discontinuation is difficult to establish (de Figueiredo and Kyle, 2006) because such dates are seldom known outside the company. Mobile device phase-outs are also complicated by retail distribution channels, which purchase phones from the manufacturers before selling them to end users. The inventory in these retail channels results in sales appearing to continue long after phones have been discontinued by the manufacturer. We therefore define *discontinuation* as the cessation of product shipments from the handset manufacturer, not as the cessation of retail sales. The data give an indication of manufacturers’ internal selection decisions in the form of a sudden and discontinuous fall in monthly sales, although they may not fall to zero. For a small subsample of devices we were able to locate data through internal company documentation that provided the exact discontinuation date.

All device phase-outs were coded manually by two individuals. Accuracy across individuals was high: for 94 percent of the devices, the coded discontinuation dates were within
three months of each other. The coding was also checked against available internal data, revealing near-perfect accuracy. For those few devices whose coded discontinuation dates were not within three months, the coders jointly revisited the available information and reached a consensus on the discontinuation date. The coders did not identify phase-outs of any devices for which the observations were either left-censored (i.e., that were already in the sample at $t = 0$, which would exclude them from the analysis) or right-censored (i.e., that may or may not have been discontinued by the end of the observation period).

**Organizational Structure and Decision Making**

Following an approach similar to that of Henderson and Cockburn (1994), we conducted a literature search to build an initial understanding of each firm’s organizational structure and decision-making processes. This search covered more than a dozen newspapers and magazines, several business case publishers, and books spanning a decade of coverage on our five focal companies: LG, Motorola, Nokia, Samsung, and Sony Ericsson. We conducted semi-structured interviews with individuals knowledgeable about the product management process in order to develop a narrative of key structural characteristics of each firm across our observation period. These interviews were approximately an hour in length; they were held in person when possible and by telephone otherwise. Interviewees were employees of the firm who were familiar with the intricacies of the product management process—by virtue of playing a product management role themselves or of interacting extensively with the organization’s portfolio management teams.

We used these initial interviews and narratives to develop a questionnaire that could be used to measure some relevant structural aspects of decision making that were common across all firms. This questionnaire specifically prompted the respondent to answer each question for each year of the study period. We developed an assessment of each firm that was based on our
narratives and then used this assessment to test the accuracy of our secondary data by sending the questionnaire to previous interview respondents at each firm for verification purposes. To measure elevation, we asked respondents questions about how often portfolio management decisions were deferred to higher-ups in the organizational structure. To measure consultation, we asked respondents whether or not portfolio management was driven by participative consensus. For each year of the study period, responses are given on a 5-point Likert scale on which 1 (resp., 5) represents the least (resp., most) elevation within the hierarchy or consultation among same-level units. The survey instrument was translated into Korean in order to facilitate interviews with Korean firms (Harkness, Pennell, and Schoua-Glusberg, 2004).

Rather than embed our two measures in a larger, “organizational structure” construct, we chose to analyze separately the effect of each structural aspect on organizational decision making. One advantage of this approach is that it parallels the theoretical difference between centralization and integration explored previously; another advantage is that it yields greater insight into the effect of each structural aspect on culling. Moreover, separating consultation from the locus of decision-making authority is consistent with our experience in assembling the qualitative data, which indicated that higher-level staff involvement in managing products varies independently of the firm’s reliance upon consultation in decision making.

**Aspiration levels and performance feedback.** Feedback consists of performance signals derived from multiple sources—in particular, one’s own historic performance and the performance of competitors within a competitive space. These sources of feedback have been classified by empirical studies as, respectively, *historical* and *social* aspiration levels (Greve, 1999). Consistent with other research on organizational learning in the context of a product portfolio, we focused initially on historical aspirations at the portfolio level (Audia and Greve,
2006). Less is known about how managers form reference groups (Greve, 1998); hence defining the social group relevant to the devices against which a manager makes comparisons would prove difficult in the mobile device industry, where devices compete—with respect to features and prices—not only within a given product generation but also across generations.

Our performance measure is based on unit sales at the portfolio level because such sales are a key performance indicator in the mobile device industry and are tracked closely by manufacturers, carriers, and analysts. Although we control for the sales performance of individual devices, our main independent variable is portfolio sales. Theoretically we are interested in portfolio feedback. During this time period, only a handful of devices (e.g., the Motorola RAZR) garnered managerial attention in excess of normal portfolio management procedures. Furthermore, “hero” devices (e.g., the Samsung Galaxy) had not yet arisen in the portfolios to which this study pertains. Portfolio unit sales are simply the total sales of all of a firm’s devices within a given period. To account for life-cycle issues in the portfolio that affect managers’ perceptions of performance relative to aspirations, we use the slope between portfolio unit sales at time $t$ and at time $t - 1$ as a measure of the percentage change in those sales. This change is our measure of performance, which is consistent with the approach taken by Audia and Brion (2007).

From a conceptual standpoint we are arguing that managers are concerned less about whether or not portfolio sales increase or decrease relative to past levels than about whether or not those sales has achieved management’s growth targets. Thus formulating aspiration levels in terms of growth accords with our product manager interviews, with internal presentations used to guide culling decisions, and with previous research (e.g., Audia and Brion, 2007) on aspirations and performance. As a robustness check we also used percentage change in portfolio total
revenue. Our results were similar under both measures, which suggests that pricing changes before discontinuation do not fundamentally alter the feedback processes examined here.

We employ a formulation similar to those used in previous studies on performance feedback (Greve 2003b; Audia and Greve, 2006) to define a historical aspiration level for product portfolio performance as follows. Let $H_{uit}$ denote the historical aspirations of firm $i$ at time $t$ at the $u$th level, where $u$ represents portfolio share, and let $P_{uit}$ denote the performance of that firm. Then historical aspiration is given by $H_{uit+1} = \alpha P_{uit} + (1 - \alpha)H_{uit}$, where the adjustment parameter $\alpha$ is chosen by searching over all parameter values—in increments of 0.1—and then using the value that produces the maximum log-likelihood (i.e., 0.8) consistent with previous studies (Cyert and March, 1963; Greve, 2003a). Our findings are generally robust to the weighting scheme.

The performance–aspiration gap is simply defined as the difference between performance and aspiration level for each of the portfolios. We implemented a spline function to compare the effects of this gap above and below the aspiration level (Greve, 2003b; Miller and Chen, 2004). This was accomplished by splitting each of the historical performance variables into two variables. Performance $\text{above}$ aspiration is set equal to zero for all observations in which the performance (at the portfolio or phone level) of the focal firm is less than its historical aspiration level, and it equals the difference between actual performance and the historical aspiration level when the firm’s performance is above that level. Thus,

$$[\text{Performance above historic aspirations}]_u(t) = \max[0, (P_{uit} - H_{uit}^u)],$$

where $u$ represents one firm’s product portfolio. Performance $\text{below}$ historic aspiration is defined symmetrically. In other words, it is set equal to zero when performance is above the aspiration level and equals the performance–aspiration gap when performance falls below that level:
[Performance below historic aspirations]\( (u) = \min[0, (P^w - H^w)] \).

All gap variables are lagged by three quarters in the empirical specification; note that Henderson and Stern (2004) also lagged key independent variables in their event history analysis of product culling behavior. Weighing the relatively frequent re-evaluation of performance results against the constraints on device life and the ramp-down time required to coordinate all aspects of the phase-out process, we decided that a lag of three quarters would be appropriate for illustrating the relationship between structure, feedback, and phase-out while maintaining acceptable temporal separation between independent and dependent variables. Given the mean product life for a mobile device consists of only 4.3 quarters on average, a longer lag structure, such as four quarters, is inconsistent with both internal review cycles and our semi-structured interviews with individuals involved in product management.

**Device sales and replacement as important factors in phase-out.** In addition to the key theoretical variables described already, two of our controls warrant special attention. First, we control for phone sales performance to account for the impact (if any) of a particular device’s sales on the choice of product(s) to be phased out of a firm’s portfolio. Thus, the interaction effects we observe between structure and feedback are beyond those associated with the sales performance of any individual device. Although this variable is included in the model as a simple control for device performance, we also tested its robustness to alternative formulations—specifically, as a feedback variable—that were consistent with observed main portfolio feedback effects.

Second, we include a control for whether or not the device has a direct replacement. Such devices can be quickly pulled from the market, regardless of performance, to make room for the replacement device. All else equal, this may affect how the phase-out decision is made and
create a constraint that transcends feedback processes. For our purposes, a *direct replacement* is one that is launched within one quarter of the previous device’s exit and that has a launch price within 10 percent of its predecessor device’s launch price. Our definition is consistent with pricing patterns observed in the industry, where devices are quickly discounted after launch and marketers tend to “tier” phone offerings into price bands. In practice, this is a fairly strict standard for what constitutes a replacement. We tested other formulations of this variable in which the window between exit and launch was lengthened to two quarters in the presence of various price differences. Our results were not affected by these alternate constructions.

**Other Controls**

Our other selected controls provide insight into alternative mechanisms that might be active in the phase-out decision process. For this study, these additional controls were motivated by interviews with product managers at the major firms, internal documentation related to culling decisions, and the relevant theoretical literature on firm decision making. We use firm sales as a proxy for size, whose effect on product exit decisions we wish to assess (cf. Hannan and Freeman, 1984; Henderson and Stern, 2004). In estimating the model, we control for a number of variables in order to isolate their impact on product discontinuation; these variables capture characteristics of the individual device, its parent firm, and the market as a whole for each period of time. Our model also includes year and firm dummies to test for robustness (see table 4).

Several firm-specific variables were also used to control for heterogeneity among participants in the marketplace—specifically, with respect to the number of 3G devices and smartphones in a firm’s portfolio—so as to capture broad improvement in underlying technologies (Greenstein and Wade, 1998; de Figueiredo and Kyle, 2006). We used a firm’s average portfolio age at each moment in time to capture the degree of portfolio obsolescence
(Henderson and Stern, 2004), and we used cash levels and current ratios (i.e., assets/liabilities) to account for different levels of slack across firms (Cyert and March, 1963).

Previous studies have employed unit counts over time to approximate experiential learning (de Figueiredo and Kyle, 2001; Henderson and Stern, 2004). We take an analogous approach when measuring capability development over time, using total number of phones launched since the start of the observation period as a metric for phone introduction capabilities. We also included measures of culling experience that are similar to those used by Sorenson (2000). Our regressions incorporated an indicator for whether or not the firm manufactures its devices in-house as well as one for whether or not it owns a semiconductor unit. These controls were meant to capture the presence (or absence) of those firm capabilities and to account for differing levels of vertical integration across firms; this is important because upstream capabilities may affect behavior in downstream markets (de Figueiredo and Teece, 1996). Finally, we controlled for both market density and the number of same-period competitive phone launches (after Sorenson, 2000; Henderson and Stern, 2004) to account for period-specific market dynamics that may drive decision making and for the extent of market crowdedness. All time-varying controls were lagged three periods so that they would be consistent with our lag structure for performance aspiration variables.

**Empirical Specification**

In order to examine the factors that affect phone life over time, we apply a piecewise exponential hazard rate model with many similarities to the approach of Sorenson and Stuart (2000) and de Figueiredo and Kyle (2001, 2006). This model accounts for right-censoring—although left-censored observations, for which we lack data on the beginning of a phone’s life, are dropped from the sample—and it offers flexibility in handling both time-invariant and time-varying
covariates. Whereas the exponential specification assumes a constant and time-invariant hazard rate, the piecewise specification enables us to apply different base hazard rates that depend on the device’s age; thus we can control for any heterogeneity in decision-making processes that is driven by age-dependent factors. The coefficients in the estimation can be viewed as generating multipliers of the appropriate underlying base hazard rate, which increases as the mobile device ages. The clock in this model is device age, and the individual device is the unit of analysis. In the piecewise analysis, our pieces are the following intervals of device age: 0–1 quarters, 1–2 quarters, 2–3 quarters, 3–4 quarters, and more than 4 quarters. A Kaplan–Meier survival graph (see figure 2) indicates that the hazard rate differs for each of these time periods, so the intervals we use lead to legitimate improvements in model fit.

*** Insert Figure 2 about here ***

Our specification follows that in Blossfeld, Golsch, and Rohwer (2007), and we assume a constant hazard rate for each interval of device age: \( r(t) = a \). The underlying survivor function within a piece is \( G(t) = e^{-at} \) and the hazard rate can be expressed as \( a_i = \exp\{x_i\beta\} \), which implies different hazard levels for different \( x_i \) observations. The model’s beta coefficients are estimated using maximum likelihood techniques.

RESULTS

Table 2 shows the piecewise exponential hazard rate results for quarterly device phase-out. Model 1 includes only the control variables, models 2 and 3 examine (respectively) the impact of organizational structure variables related to elevation and consultation, model 4 examines both impacts jointly, model 5 shows the effects of performance feedback, models 6 and 7 show the interaction between performance feedback and the organizational structure variables, and model 8 shows all main effects and interactions together. The baseline model exhibits a highly
significant fit to the data (a chi-square test reveals $p < .001$). The inclusion of both structural characteristics yields significant improvement in model fit for models 2 and 3, as indicated by the significant coefficient for these variables. In model 4 the change in $\chi^2$ over the base model 1 is 5.48, which is below a $p < .01$ threshold for increase in model fit. This finding suggests that the two structure elements jointly yield a significantly better fit to our data than does either element independently. To interpret the magnitude of the coefficients appearing in table 2, we calculated the effect that a one standard deviation change on our measures of elevation and consensus would have on the instantaneous hazard rate based on the main effects reported in table 2, model 4. In addition to being statistically significant, the practical significance of a change in structure is quite large, the instantaneous hazard rate changing by 28 and 35 percent in response to a one standard deviation change on our measures of elevation and consensus, respectively. Moreover, the models that include interactions between structure and feedback exhibit a noticeable improvement in fit over baseline models that incorporate performance feedback only (for models 6, 7, and 8; $p < .001$). Figure 3 summarizes our hypotheses and results.

*** Insert Table 2 about here ***

*** Insert Figure 3 about here ***

In model 1, we find that competitive density drives an increased rate of product turnover and that the presence of a replacement device leads to a quicker rate of product exit. These results are consistent with our qualitative interviews, which suggested that managers actively engage in scanning the competitive landscape and juggling different generations of products. We find highly significant results on device-level performance, confirming the intuition that culling is strongly influenced by the unit sales of individual devices.
We also find a significant effect on size (measured in terms of corporate sales), which is associated with reduced product culling. This result echoes the literature addressing the effect of organizational inertia on adaptation and innovation (Hannan and Freeman, 1984), as the organizational inertia associated with increased size has the effect of slowing down the rate of product culling. Contrary to results in Sorenson (2000) and Henderson and Stern (2004), the coefficient for our “experience” variable is not significant; in other words, current culling rates seem largely unrelated to previous rates in the same market. There are numerous reports of the difficulties that traditional mobile device firms encountered when adjusting to the demands of new technologies such as 3G (for a description of Nokia’s struggles in this area, see Troianovski and Grundberg, 2012). Note also that the rate of product turnover (4.3 mean quarters of life) was much higher in our study than in that of Sorenson (2000), who examined workstations (2.84 mean years of life), and Henderson and Stern (2004), who examined personal computers (2.31 mean years). These considerations explain why an experience variable, which captures learning over a long period of time, may be less relevant in our context than in previous studies.

It is interesting that these two technological developments had the opposite effect on hazard rates. Whereas increasing the number of 3G devices in a product portfolio reduced hazard over time, additional smartphones were associated with an increased hazard rate. This result may reflect key differences in these technologies: acceptance of the 3G standard was instrumental in the widespread use of smartphones, but no dominant designs emerged for such devices until after the sample period. Consequently, handset manufacturers may have been forced to cull early-launch smartphones at a higher rate while consumer preferences were evolving.

Model 2 adds the elevation measure to our culling model. Hypothesis 1 argued that elevation will generally speed culling because higher-level managers can more quickly transfer
resources from one product to another. Consistent with H1, we find a statistically significant coefficient for elevation in model 2; that coefficient is significant and positive excepting only in models 4 and 7, which indicates that higher elevation is associated with increased culling. Even in models 4 and 7, the effect of elevation on phase-out remains significant at the 10 percent level.

Model 3 shows the main effect of consultation on the culling model. Hypothesis 2 argued that, when consensus is required, more bargaining occurs and more trade-offs are made; these factors should result in products being left on the market longer, on average, despite product managers’ efforts to move on to the next generation. We thus expect the sign on the consultation variable’s coefficient to be negative. Our results corroborate this hypothesis: in model 3 we find a statistically significant negative coefficient for consultation, indicating that increased consultation is associated with slower phase-out. This finding is robust and significant ($p < .01$) in models 4, 6, 7, and 8.

Model 5 shows how our measures of portfolio-level performance feedback affect product phase-out. Consistent with H3a and H3b, we find that performance both above and below aspirations is associated with a slower rate of product phase-out. This finding accords with our argument that product management faces pressures driven by the continued commitment to previously made decisions and by both internal and external attributions of product success or failure.

Models 6, 7, and 8 show the results when structure interacts with feedback. Model 6 shows feedback being moderated by elevation, model 7 shows it moderated by consultation, and model 8 combines both of these variables. Following Sorenson (2000), we simultaneously add each term and its interaction to our models. It is important to note that the “main effect” of feedback cannot be interpreted as simply the coefficient for the portfolio-level feedback variable
(Jaccard and Turrisi, 2003). As these authors stated, the coefficient for the main effect represents its influence when the other term in the interaction is zero. In our sample, the zero value is meaningless, as it does not occur, as consultation and elevation vary from 1 to 5. We find a negative effect of portfolio feedback on culling when performance is above aspirations. Models 6–8 exhibit similar main effects of the structural variables as in models 2 and 3, and—for performance above aspirations—each effect in the interaction models is preserved when both sets of interactions are run simultaneously.

The formal tests for hypotheses 3a, 3b, 4a, 4b, 5a, and 5b amount to examining the regression output (table 2) and comparing it against our expected signs for these variables (figure 3). Models 6–8 corroborate our hypotheses, though with only partial support for H4b. Observe that the model with both sets of interactions is the one that best fits the data when we compare models 2 and 3 to models 6–8; this is our direct comparison of the “main effect” models with the “moderating factor” models that include portfolio feedback effects (the chi-square statistic for this comparison is significant at \( p < .001 \)). We take the outcome of this test to mean that structural characteristics explain culling better when considered jointly than individually.

To facilitate the interpretation of these findings, we have separately graphed the key results of models 6 and 7 in figures 4 and 5, respectively. The \( x \)-axis of these figures marks performance relative to aspirations, and the two are equal at the center of this axis. In each figure, the \( y \)-axis represents the (log of the) multiplier of the hazard rate of phase-out (cf. Davis and Greve, 1997); when this value is greater (less) than 1, the likelihood of phase-out increases (decreases). Two lines representing different values of elevation and consultation are plotted in this graph of figures 4 and 5, respectively. Thus the graphs show how elevation and consultation affect the rate of phase-out at different levels of performance relative to aspirations. The domain
of each graph is approximately ±1 standard deviation from the mean for performance relative to aspirations suggesting that the entire domain is relevant for analysis. The chosen values of elevation and consultation are also within the data range. The interaction terms for both elevation and consultation are significant in models 6 and 7: all of the displayed slopes are statistically different from zero. However, Figure 5 shows that, at certain points in the structure–performance space, the multiplier of the hazard rate is 1 (i.e., no net effect).

*** Insert Figure 4 about here ***

Figure 4, which plots elevation against performance relative to aspirations, is the source of several striking results. It is most interesting that the response to feedback depends on where decision rights reside in the organization. The net effect of performance feedback can be either to hasten or delay phase-out, which suggests an interesting link between the behavioral mechanism of performance feedback and the structure of a firm’s decision making. In particular, the right hand side of figure 4 shows a range of performance less aspirations in which a lower degree of elevation is associated with a higher rate of product phase-out.

Three other observations are warranted by examining figures 4 and 5. First, the multiplier of the hazard rate is lower at higher levels of performance relative to aspirations. This dynamic is consistent with hypotheses 3a and 3b. In the context of figure 4, our hypotheses 4a and 4b suggest that the hazard rate multiplier declines the most when elevation is highest. A comparison of the slopes of both level curves of elevation clearly demonstrates this. When performance equals aspirations, the multiplier is larger when elevation is higher. Yet at moderate levels of performance above aspiration, the multiplier is smaller for higher than for lower elevation; this is the effect of the plot for performance above aspirations being steeper when elevation is high, consistent with H4a. A similar pattern is present with respect to H4b when we compare the slope.
of the lines where elevation = 5 to elevation = 3 on the left-most graph; here the effect is less
dramatic, however, and is insignificant at the 5% level in the full model.

*** Insert Figure 5 about here ***

Figure 5, which addresses consultation, appears to be less variable than its elevation
counterpart (figure 4), though the regression output suggests that both interactions between
performance feedback (i.e., either above or below aspirations) and consultation are significantly
different from zero. The range of figure 5 is strictly less than 1; this suggests that, in the
displayed performance feedback–consultation domain, the net effect of these variables is to slow
phase-out. Consistently with H2, at higher levels of consultation we find a lower multiplier of the
hazard rate: both lines where consultation = 5 are lower than the lines where consultation = 3 for the range of the data.

Altogether these results suggest that, under different conditions of portfolio growth, the
configuration of the organization with the greatest net increase or decrease in culling might be
dramatically different. In particular, our results indicate that phase-out is most rapid in firms that
outperform aspirations and for whom decision rights are relatively decentralized to lower-level
managers. However, the opposite holds when portfolio performance is below aspirations:
elevation of decisions to those higher in the hierarchy is associated with increased culling.

**Sensitivity Analysis**

In this section we explore the sensitivity of our findings to two alternative specifications: one in
which the independent variable for performance feedback is formulated using revenue figures;
and one in which firm and year dummy variables are included, as is common in product-level
analyses.
**Alternative formulation of performance feedback variables.** In order to assess the robustness of our results to alternative explanations, we have included a number of robustness and sensitivity tests to ensure that the observed patterns involving organizational architecture and performance feedback are consistent across specifications. First, performance feedback is usually measured with respect to more than one organizational goal (Cyert and March, 1963). We have therefore recalculated our results, which were obtained from sales figures, while using revenue figures instead. Table 3 shows the results when models 1–7 are recalculated based on revenue.

*** Insert Table 3 about here ***

Overall, the results are consistent with those reported in table 2. This suggests that pricing strategies do not significantly alter the nature of the feedback process that occurs at the portfolio level of aggregation. We believe that the results determined from sales figures are more reliable; the reason is that revenue figures must be based upon a single price estimate because our data are not such that we can disaggregate the pricing strategy of individual retailers. Hence one should expect more measurement error in the revenue variables, which would bias our findings toward non-significance. The revenue approach yields smaller log-likelihood figures, which indicates that models based on unit sales better fit the data. This explains why we have chosen to emphasize results based on the latter approach, though we remain encouraged by the fairly consistent results across the different formulations.

**Year and firm dummies.** Next we incorporate both firm and year dummies to account for organizational and temporal idiosyncrasies—for instance, time-invariant firm characteristics or accelerating technological advancement—that may broadly affect phase-out patterns. Both year and firm dummies are commonly used in models of product management (de Figueiredo and Kyle 2001). Table 4 shows the results of adding these effects sequentially: first the firm dummy
and then the year dummy. These models also parse out the effect of organizational structure on measurement of the key variables, demonstrating that our main results hold even when we control for cross-firm differences in measurement.

*** Insert Table 4 about here ***

When these dummies are included in the regression, the results are virtually identical to those reported in table 2, model 8. The interaction between consultation and performance above aspirations is no longer significant at the $p < .05$ level, but with year and firm fixed effects the $p$-value is .052 and remains significant at the 10 percent level. Note that incorporating firm and year dummies does not improve the model’s statistical fit. It is therefore reasonable to conclude that a model excluding these parameters yields a statistically similar and thus adequate fit to the data, which supports our decision to omit these effects from the model’s original formulation.

**DISCUSSION**

This study develops a model of situated selection to explain the effects of organizational structure on persistence in product phase-out. In particular, we examine the effects of decision-making elevation and consultation on product phase-out in the mobile device industry. Our results suggest that decision makers at lower levels of the hierarchy are constrained in their ability to coordinate the various activities required for phase-out and thus in their tendency to cull products more slowly. In contrast, when phase-out decisions are made at higher levels, the decision makers have better information, are less encumbered by parochial agendas, and are better situated to recognized interdependencies among product teams and to support products that succeed in the marketplace. Yet higher-level managers are also more prone to inertial forces and attributional biases and tend to favor the status quo. This is because their attention is focused at the portfolio level, not the product level, an orientation that is driven in part by the demands of
external constituents and their separation from product market activities. As a result, we observe persistence in the product portfolio when its performance is especially high or low.

We also find that, in a structure under which decision-makers engage in relatively less consultation with other managers, product life is typically shorter because bargaining is less prevalent and negotiated trade-offs are less likely to occur. In such cases, managers are required neither to secure others’ approval for product proposals nor to accommodate the often divergent interests of the managers responsible for competing products. In contrast, consensus-driven environments delay phase-out when portfolio performance is above aspirations because that success is attributed to the collectively established decisions. Yet when performance is below aspirations, a consultative environment may encourage more debate and a willingness to question prevailing explanations of that underperformance, resulting in faster phase-out.

Our study makes several contributions. First, we offer new insights into the determinants of product phase-out. Much of the research on product exit points to drivers that are economic (Greenstein and Wade, 1998) or based on prior experience (Henderson and Stern, 2004). We add to this research by highlighting the importance of organizational structure. In particular, our emphasis on its role in situating phase-out decisions at lower levels—and in absence of other managerial input—presumes that selection is, in practice, a more local determination than previously considered. Implicit in much of the seminal research (e.g. Burgelman, 1991) is that internal selection environments are relatively homogeneous, so these studies largely ignore variations in where and how decisions are made. Our study of leading mobile device firms reveals that the locus of decision making varies, and we posit that selection patterns may vary as a result. Selection decisions do not always reside at the lowest levels; in some cases, they reside quite high in the hierarchy. At Motorola, for example, in 2009 the CEO and head of the mobile
devices unit sought to clear out the entire portfolio in attempting to help save the division. We offer a model of situated selection that accommodates the diversity, within and across firms, in decision procedures.

Our study also underscores the distinction between hierarchical and consultative decision making. Much of the research on centralization and decentralization implicitly equates the mere presence of decentralization with greater interactions between managers; however, we do not make this assumption. In fact, we discover that product phase-out is delayed unless portfolio decisions are made at the firm’s lower levels and middle managers have much discretion. Thus our findings highlight the key role of middle managers (cf. Huy, 2002), and support research that suggests the attention-directing qualities of structural differentiation (but not integration) may increase adaptability (Ethiraj and Levinthal, 2004; Joseph and Ocasio, 2012).

Second, this study links behavioral theories of performance feedback to organizational structure as a means to explain the complexity of phase-out decisions and the implications for persistence behavior following perceptions of success and failure. In doing so, we have augmented the growing scholarship on performance feedback by considering some important conditional effects imposed by elevation and consultation in decision making. The role of organizational structure has been notably absent in studies of performance feedback (Gaba and Joseph, 2012), and our study suggests that more research linking cognitive and structural explanations for adaptive behavior is in order. Moreover, it is clear from our results that the forces inducing persistence are not dispersed uniformly throughout the firm, and more work exploring such differences could be illuminating. In a related vein, our study also augments models of shared cognition that focus on the performance implications of broadly diffused mental models, schemas, frames, and logics (Eggers and Kaplan, 2009; 2013). Here we suggest
that capabilities may be created not through shared cognition but through situated cognition: the spatial and temporal conjunction of certain players and types of feedback.

By extension, this paper documents that the role of organizational structure in decision making involves more than information processing. In particular, we establish the effect of structure on situated decision making and demonstrate that responses to performance feedback vary with the elevation of and consensus sought in decision making. Organizational structure situates cognition and hence variations in perceptions, interpretations, and responses to performance feedback. Our study is consistent with recent research suggesting that cognitive biases may be affected, and in some cases circumvented, by the organizational context in which learning and decision making occur (Lave and Wenger, 1991; Elsbach, Barr, and Hargadon, 2005). These studies argue that contextual dimensions—such as organizational culture (Edmondson 1999, Bunderson and Sutcliffe, 2003), social identity (Kane, Argote, and Levine, 2005), and organizational processes (McNamara and Bromiley, 1997)—interact with cognitive factors to situate learning processes and alter outcomes (Argote and Todorova, 2007). For instance, McNamara and Bromiley found that both organizational and cognitive factors influence risky decision making but that, when both are present, organizational factors (e.g., goals) tend to dominate cognitive biases. This means that models of decision making and cognition may be inaccurate in their predictions of real-life processes, such as internal selection, if they fail to consider such important situational factors (Lant, 2002) as the decision-making structure of complex organizations. The new insights we provide on this score suggesting that the importance of structure may lie not only in its capacity for responding to environmental complexity, speeding decisions, and processing information—as documented in prior research—but also in its ability to shape the context in which portfolio decisions are made.
This also points to one of the limitations of the study in that we examine a very specific period in the mobile device industry. This was a period of great turbulence and technological change since no dominant design had yet emerged and 3G technology was in its infancy. The iPhone was launched toward the end of our sample period and the network externalities provided by the Android and iOS operating systems had yet to emerge. In addition, the global mobile device industry has relatively few large players; it may be that a fragmented industry with many small players characterized by flat hierarchies exhibits no significant effects for the level of decision making. Second, because top management focuses on a host of goals, future research should consider the consequences of attention to multiple simultaneous goals at both the corporate and business unit level. It may also be that the degree to which goals are interdependent has measurable consequences (Ethiraj and Levinthal, 2009). Highly correlated goals may lead to different outcomes than goals derived from performance measures that are either uncorrelated or negatively correlated. Third, we studied only the five major participants in this industry because we lacked accurate historical structural data for the sample firms that were less active in the mobile device arena. Future research might usefully investigate whether the level of decision making and the extent of consultation during that process account for meaningful variance in smaller firms, too. Fourth, our study controls for phone replacement but captures the impact of architecture on only one aspect of the product management cycle: the decision to phase out a product. Applying an event history methodology to a study of entry is complicated by the difficulties in establishing when a particular observation enters the risk set (Nerkar and Paruchuri, 2005). Neither of the conventional solutions proposed to address this issue yields an adequate resolution. A Poisson model of entry by period is a less intuitive match to the rate of decision making and so introduces many other, unobservable decision factors; and
establishing entry into the risk set as a function of the time delay between first and second iterations of a product type is untenable given the nature of technical progress in this industry. New ideas and work on this problem would be welcome.

**CONCLUSION**

From the managerial perspective, our model of decentralized autonomy may be the most suitable approach if rapid phase-out is required. However, managers under these conditions may miss the full life cycle of products, prematurely phasing out products that could still contribute to the firm’s bottom line. It is worth noting that Apple, when controlled by Steve Jobs, was quite successful in a decision-making environment that was centralized and not based on consensus. However, the business model of Apple was much different from that of the large manufacturers (e.g., Nokia and Samsung) and led to very few product introductions, which made phase-out less of a concern.

For scholars, a broader contribution of this paper is to link key pillars of the Carnegie School: hierarchy, aspirations and cooperation. These three pillars have been largely developed independently, yielding a wealth of theory for each that is largely void of the other two. This study integrates them in support of Neo-Carnegie scholars who call for a focus on “renewed behaviorally plausible, decision-centered perspective on organization” (Gavetti, Levinthal and Ocasio, 2007: 525). To that end, we offer a situated decision-making theory of organizational choice, which integrates hierarchy, aspirations and cooperation amidst conflicting interests, and provides a sharper relief of persistence in organizations.
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Table 1. Summary Statistics and Cross-Correlations (N = 1307 product-quarters)

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<td>-0.26</td>
<td>-0.24</td>
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<td>-0.59</td>
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<td>14 # of competitors phones on market+</td>
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<td>22.69</td>
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+: Lagged by three quarters

All correlations larger in magnitude than .074 are significant at the 5% level
Table 2. Piecewise Exponential Hazard Rate Models for Product Exit

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<th>(1) Unit Sales</th>
<th>(2) Unit Sales</th>
<th>(3) Unit Sales</th>
<th>(4) Unit Sales</th>
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<th>(6) Unit Sales</th>
<th>(7) Unit Sales</th>
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<td>1 Elevation+</td>
<td>0.255*</td>
<td>0.222</td>
<td>0.484**</td>
<td>0.217</td>
<td>0.344*</td>
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<tr>
<td>2 Consultation+</td>
<td>-0.320**</td>
<td>-0.294**</td>
<td>-0.316**</td>
<td>-0.486***</td>
<td>-0.478***</td>
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<td>3 Portfolio level - Perf. Above Aspirations+</td>
<td>-0.718*</td>
<td>18.07***</td>
<td>2.585</td>
<td>19.99***</td>
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<td>4 Portfolio level - Perf. Below Aspirations+</td>
<td>0.969***</td>
<td>-0.838</td>
<td>3.338***</td>
<td>2.451**</td>
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<td>5 Elevation * P&gt;A</td>
<td>0.969***</td>
<td>-0.838</td>
<td>3.338***</td>
<td>2.451**</td>
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<td>6 Elevation * P&lt;A</td>
<td>0.653***</td>
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<td>7 Indicator: Phone has a direct replacement</td>
<td>1.111**</td>
<td>1.179***</td>
<td>0.950**</td>
<td>1.012**</td>
<td>1.344***</td>
<td>1.242***</td>
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<td>9 Device Sales (000s)+</td>
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<td>-0.010***</td>
<td>-0.009***</td>
<td>-0.009***</td>
<td>-0.000***</td>
<td>-0.010***</td>
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<td>12 Average Portfolio Age+</td>
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<td>14.01</td>
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<td>17.80*</td>
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<td>0.001</td>
<td>0.000</td>
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<td>Piece 4: 3Q-4Q phone life</td>
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<td>5.081</td>
<td>-2.647</td>
<td>0.754</td>
<td>3.832</td>
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Log-likelihood 140.67 142.64 144.66 146.15 164.78 187.88 187.05 201.08
Standardized beta coefficients * p<0.05 ** p<0.01 *** p<0.001 +: Lagged by three quarters
Table 3. Models 1-7, demonstrating robustness to revenue formulation of portfolio performance-feedback variables

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<th>Piecewise Exponential Hazard Rate Models (Exit)</th>
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<td>0.420**</td>
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<td>-0.356**</td>
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<td>11 Experience: Degree of Culling+</td>
<td>-0.212</td>
<td>-0.418</td>
<td>-0.0714</td>
<td>-0.254</td>
<td>-0.190</td>
<td>-0.309</td>
<td>-0.273</td>
<td>-0.333</td>
</tr>
<tr>
<td>12 Firm Sales (MMs) +</td>
<td>-0.003*</td>
<td>-0.003*</td>
<td>-0.003*</td>
<td>-0.003*</td>
<td>-0.000*</td>
<td>-0.003*</td>
<td>-0.004**</td>
<td>-0.003*</td>
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<tr>
<td>13 # of 3G phones in Portfolio</td>
<td>-0.194</td>
<td>-0.333*</td>
<td>-0.0585</td>
<td>-0.181</td>
<td>-0.244</td>
<td>-0.217</td>
<td>-0.259</td>
<td>-0.214</td>
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<tr>
<td>14 # of Smartphones in Portfolio</td>
<td>0.185</td>
<td>0.307*</td>
<td>0.0428</td>
<td>0.152</td>
<td>0.233</td>
<td>0.189</td>
<td>0.230</td>
<td>0.189</td>
</tr>
<tr>
<td>15 Average Portfolio Age+</td>
<td>-0.433*</td>
<td>-0.295</td>
<td>-0.491*</td>
<td>-0.371</td>
<td>-0.460*</td>
<td>-0.446*</td>
<td>-0.512*</td>
<td>-0.570**</td>
</tr>
<tr>
<td>16 Cumulative phone launches+</td>
<td>-0.011</td>
<td>-0.021*</td>
<td>-0.000</td>
<td>-0.009</td>
<td>-0.013</td>
<td>-0.007</td>
<td>-0.013</td>
<td>-0.005</td>
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<tr>
<td>17 Vertical integration: Has semiconductor</td>
<td>14.01</td>
<td>14.69</td>
<td>17.11*</td>
<td>17.80*</td>
<td>14.49*</td>
<td>16.95*</td>
<td>18.78**</td>
<td>16.02*</td>
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<tr>
<td>18 # of competiors phones on market+</td>
<td>0.001</td>
<td>0.001</td>
<td>0.000</td>
<td>0.000</td>
<td>-0.001</td>
<td>-0.002</td>
<td>-0.002</td>
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<tr>
<td>19 # of competitive launches+</td>
<td>0.016*</td>
<td>0.017**</td>
<td>0.015*</td>
<td>0.017**</td>
<td>0.011</td>
<td>0.013*</td>
<td>0.011</td>
<td>0.012</td>
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<tr>
<td>Piece 4: 3Q-4Q phone life</td>
<td>1.369</td>
<td>5.081</td>
<td>-2.647</td>
<td>0.754</td>
<td>3.319</td>
<td>2.502</td>
<td>3.211</td>
<td>2.408</td>
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<tr>
<td>Piece 5: 4Q+ phone life</td>
<td>2.172</td>
<td>5.887*</td>
<td>-1.831</td>
<td>1.574</td>
<td>3.766</td>
<td>2.999</td>
<td>3.651</td>
<td>2.889</td>
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<tr>
<td>N</td>
<td>1307</td>
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<td>1307</td>
<td>1307</td>
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<tr>
<td>Log-likelihood</td>
<td>140.67</td>
<td>142.64</td>
<td>144.66</td>
<td>146.15</td>
<td>161.29</td>
<td>177.28</td>
<td>183.25</td>
<td>189.87</td>
</tr>
</tbody>
</table>
| Standardized beta coefficients                  | * p<0.05 ** p<0.01 *** p<0.001                         | +: Lagged by three quarters
Table 4. Replication of Table 2, Model 8, including year and firm dummies

<table>
<thead>
<tr>
<th>Piecewise Exponential Hazard Rate Models (Exit)</th>
<th>(1) Unit Sales</th>
<th>(2) Unit Sales</th>
<th>(3) Unit Sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Elevation+</td>
<td>0.360*</td>
<td>0.307*</td>
<td>0.394*</td>
</tr>
<tr>
<td>2 Consultation+</td>
<td>-0.388**</td>
<td>-0.501***</td>
<td>-0.322*</td>
</tr>
<tr>
<td>3 Portfolio level - Perf. Above Aspirations+</td>
<td>38.96***</td>
<td>40.45***</td>
<td>40.04***</td>
</tr>
<tr>
<td>4 Portfolio level - Perf. Below Aspirations+</td>
<td>0.229</td>
<td>0.312</td>
<td>0.446</td>
</tr>
<tr>
<td>6 Elevation * P&lt;A</td>
<td>-0.301</td>
<td>-0.305</td>
<td>-0.334</td>
</tr>
<tr>
<td>7 Consultation * P&gt;A</td>
<td>-0.655</td>
<td>-0.731*</td>
<td>-0.647</td>
</tr>
<tr>
<td>8 Consultation * P&lt;A</td>
<td>-0.552***</td>
<td>-0.538***</td>
<td>-0.522***</td>
</tr>
<tr>
<td>9 Device Sales (000s)+</td>
<td>-0.010***</td>
<td>-0.010***</td>
<td>-0.010***</td>
</tr>
<tr>
<td>10 Indicator: Phone has a direct replacement</td>
<td>1.406***</td>
<td>1.306***</td>
<td>1.238**</td>
</tr>
<tr>
<td>11 Experience: Degree of Culling+</td>
<td>-0.0648</td>
<td>-0.276</td>
<td>0.229</td>
</tr>
<tr>
<td>12 Firm Sales (MMs) +</td>
<td>-0.003**</td>
<td>-0.003**</td>
<td>-0.003**</td>
</tr>
<tr>
<td>13 # of 3G phones in Portfolio</td>
<td>7.267</td>
<td>-0.171</td>
<td>8.272</td>
</tr>
<tr>
<td>14 # of Smartphones in Portfolio</td>
<td>-8.483</td>
<td>0.151</td>
<td>-9.613</td>
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<tr>
<td>15 Average Portfolio Age+</td>
<td>-0.268</td>
<td>-0.445*</td>
<td>-0.171</td>
</tr>
<tr>
<td>16 Cumulative phone launches+</td>
<td>0.080**</td>
<td>-0.007</td>
<td>0.010***</td>
</tr>
<tr>
<td>17 Vertical integration: Has semiconductor</td>
<td>-3.806</td>
<td>14.50*</td>
<td>-5.348</td>
</tr>
<tr>
<td>18 # of competitors phones on market+</td>
<td>-0.003</td>
<td>0.000</td>
<td>0.001</td>
</tr>
<tr>
<td>19 # of competitive launches+</td>
<td>0.008</td>
<td>0.009</td>
<td>0.008</td>
</tr>
<tr>
<td>Firm Dummies?</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year Dummies?</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>N</td>
<td>1307</td>
<td>1307</td>
<td>1307</td>
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<tr>
<td>Log-likelihood</td>
<td>208.61</td>
<td>203.09</td>
<td>211.59</td>
</tr>
<tr>
<td>Standardized beta coefficients</td>
<td>* p&lt;0.05 ** p&lt;0.01 *** p&lt;0.001</td>
<td>+: Lagged by 3 quarters</td>
<td></td>
</tr>
</tbody>
</table>

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Figure 1. Histogram of phone life in quarters for LG, Motorola, Nokia, Samsung, and Sony Ericsson

Figure 2. Kaplan-Meier survival graph – each discontinuity is one quarter
Figure 3. Summary of hypotheses

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Expected Model Sign</th>
<th>Graphic Depiction</th>
<th>Support</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Phase-out increases with the elevation of product portfolio decisions.</td>
<td>+</td>
<td><img src="image" alt="Graph" /></td>
<td>Yes</td>
</tr>
<tr>
<td>2 Phase-out decreases as the extent of within-level consultation increases.</td>
<td>-</td>
<td><img src="image" alt="Graph" /></td>
<td>Yes</td>
</tr>
<tr>
<td>3a The elevation of portfolio decisions amplifies the extent to which above-aspiration level portfolio performance decreases phase-out.</td>
<td>-</td>
<td><img src="image" alt="Graph" /></td>
<td>Yes</td>
</tr>
<tr>
<td>3b The elevation of portfolio decisions amplifies the extent to which Below-aspiration level portfolio performance decreases phase-out.</td>
<td>+1</td>
<td><img src="image" alt="Graph" /></td>
<td>Partial</td>
</tr>
<tr>
<td>4a The consultation in portfolio decisions amplifies the extent to which above-aspiration level portfolio performance reduces phase-out.</td>
<td>-</td>
<td><img src="image" alt="Graph" /></td>
<td>Yes</td>
</tr>
<tr>
<td>4b The consultation in portfolio decisions attenuates the extent to which below-aspiration level portfolio performance reduces phase-out.</td>
<td>-1</td>
<td><img src="image" alt="Graph" /></td>
<td>Yes</td>
</tr>
</tbody>
</table>

1 Sign flipped because performance < aspirations is coded as a negative value.
Figure 4. The effect of performance relative to aspirations and elevation on product phase-out. Solid and dotted lines are where elevation equals 3 and 5, respectively.
Figure 5. The effect of performance relative to aspirations and consultation on product phase-out. Solid and dotted lines are where elevation equals 3 and 5, respectively.