Organizational Structure and Performance Feedback: Centralization, Aspirations, and Termination Decisions

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This study examines the effects of organizational structure and performance feedback on termination decisions—in particular, product phaseout. Using quarterly product-level data on the major mobile handset manufacturers for the period 2004–2009, we analyze how product-level feedback affects product phaseout and how these decisions are conditioned by organizational structure—the extent to which decision making is centralized. We argue that such structure affects termination in two ways: directly, through coordination, and indirectly, by shaping the interpretation of performance feedback. Our baseline models indicate that as performance increases above aspirations, the rate of phaseout decreases. We find that as performance declines below aspirations, the rate of phaseout decreases, but then increases when the product falls below a certain sales threshold. We also find evidence that centralization amplifies the feedback effect above aspirations but attenuates it below aspirations. This study links two pillars of the Carnegie school, aspiration levels and hierarchy, to explain the complexity of phaseout following perceived success or failure. We thereby augment the growing scholarship on performance feedback by considering some important conditional effects imposed by a centralized structure. Our focus on centralization expands the scope of theory concerning organization design by linking structure and cognition to explain firm behavior, especially termination decisions.

Keywords: organizational structure; behavioral theory of the firm; performance feedback; organizational design; organization and management theory

History: Published online in Articles in Advance September 2, 2016.

Introduction
This study examines the effects of organizational structure and performance feedback on product phaseout. Product phaseout is part of a broader category of termination decisions that includes decisions to dissolve organizational units (Mitchell 1994), halt investments (McGrath and Nerkar 2004, Guler 2007), abandon practices (Greve 1998, Gaba and Dokko 2015), sell off units (Hayward and Shimizu 2006, Karim 2006, Desai 2016, Vidal and Mitchell 2015), end alliances (Heimeriks et al. 2015), and exit technologies (Eggers 2012). Termination decisions are an important aspect of firm evolution; they bear on a firm’s competencies and survival (Schoonhoven et al. 1990). Product termination figures prominently in high-tech industries, where firms must respond to changing markets by actively managing their product portfolios (Henderson and Stern 2004, de Figueiredo and Kyle 2006). Although the mechanisms driving new product introductions have been studied widely (see Brown and Eisenhardt 1995), much less is known about the drivers of product phaseout.

The problem with product phaseout, and termination decisions more generally, is that managers are boundedly rational (Simon 1955) and, when deciding whether to terminate or retain activities, rely on noisy performance signals (Benner and Tripsas 2012, Posen and Levinthal 2012). These decisions can thus be affected by perceptions of product success or failure, which suggests the behavioral theory of the firm as a suitable lens through which to view such decisions (Cyert and March 1963, Greve 2003, Bromiley 2005). Behavioral theories of performance feedback demonstrate that organizations persist with successful activities (Audia et al. 2000) but change their activities following perceived failure (Baum and Dahlin 2007). Although there is considerable support for models of performance feedback (see Shinkle 2012), their explanatory potential for decisions—such as termination—is limited by assumptions concerning the interpretation of feedback information. In general, performance feedback studies draw their conclusions from the implicit assumption that feedback is invariantly assessed regardless of the structures within which decisions are made. Largely absent from these accounts is the role played by formal organizational structure—whether decision making is centralized or decentralized.
Yet organizational structure may have significant implications for termination decisions within large vertical hierarchies because it influences both the nature of information processing and the assessment of performance feedback. Structure’s role in information processing is a well-established one in that it can facilitate the efficient collection, processing, and distribution of information intended to help managers make decisions (Galbraith 1974, 1977; Tushman and Nadler 1978). Concerns about information processing have remained central to management research, with particular attention given to the coordination (Burton and Obel 2004, Puranam et al. 2012) and screening properties (Csaszar 2012, Christensen and Knudsen 2010) of different organizational structures.

Less known is how organizational structure affects responsiveness to performance feedback. A few studies have examined how different subunits within a firm may have distinct reactions to their respective feedback. (Audia and Sorensen 2001, Vissa et al. 2010, Gaba and Joseph 2013, Sengul and Obloj 2014). Audia and Sorensen (2001) examined the outcomes that follow from different subunits’ feedback. Similarly, Gaba and Joseph (2013) focused on the unique responses that follow from vertically differentiated corporate and divisional feedback. However, these studies focused on how subunits respond to their respective feedback; thus, they left open the question of how the exact same feedback is processed by different organizational structures. That question is the subject of our analysis.

In this study, we examine the effect of structure on termination by concentrating on centralization versus decentralization of decision making—whether or not decisions must be elevated to higher levels within the hierarchy. Our main thesis is that structure affects termination in two ways: directly, through vertical information flow; and indirectly, through performance assessment. We argue that firm responses to success and failure—specifically, to performance above and below aspirations—may differ as a function of the extent of (de)centralization because of corresponding differences in problem-solving processes. According to the attention-based perspective, organizational structure segments attention and shapes the cognitive strategies through which problems and solutions are identified (Ocasio 1997). Organizational structure may thus condition problemistic search behavior and responses to feedback.

We test our predictions using a data set of product sales in the German mobile device industry for 2004–2009, a period that was part of the “feature phone era.” Our main effects models indicate that as performance increases above aspirations, the rate of phaseout decreases. We find that as performance declines below aspirations, the rate of phaseout decreases but then increases when the product falls below a certain sales threshold. We also find that centralization amplifies the feedback effect above aspirations but attenuates it below aspirations.

This study makes three contributions to the literature. First, we apply a new theoretical lens to the important issue of termination decisions. We address the role of performance feedback, given that termination decisions may be especially challenging owing to the uncertainty involved. Organizational structure has also been overlooked in prior studies of termination decisions, in spite of the empirical regularity with which many such decisions occur in complex organizations. Second, we augment theories of performance feedback by elaborating the conditioning role of organizational structure. Despite its obvious importance, the structure within which a decision is made is a contextual feature that remains largely unexplored in the performance feedback literature. This paper seeks to reduce that gap by linking theories of attention (Ocasio 1997, Ocasio 2011) and performance feedback (Bromley 2005, Greve 2003) to provide a structure–feedback model of firm behavior in the context of termination decisions. More generally, our findings offer new insights into how structural and attentional drivers interact to shape adaptive behavior, of which phaseout is but one example. Little is known about this aspect of organizational design, so explorations along these lines answer the call of scholars to understand the cognitive implications of different structural arrangements and reintegrate organizational structure into the behavioral foundations of the Carnegie tradition (Gavetti et al. 2007).

Performance Feedback and Termination Decisions

Performance feedback theory is based on the premise that decision makers rely on feedback when identifying the problems to which they should attend. In models of performance feedback, boundedly rational decision makers simplify performance evaluations by transforming a continuous measure of performance into a discrete measure of success or failure (Lant 1992). To do so, decision makers compare their performance along an important dimension to an aspiration level, which serves as a dividing line between perceived success (gain) and failure (loss). Hence, decisions—such as termination—follow from comparisons that suggest product performance is either above or below that aspiration level.

When product performance increases above the aspiration level, the product is likely to be retained by the organization. Managers tend to persist with actions previously associated with favorable outcomes (Audia et al. 2000), because success creates confidence in existing knowledge and biases decisions against changes (Greve 1998) or novel alternatives (Denrell and March 2001, Posen and Levinthal 2012). Moreover, product success
serves to reinforce that the firm’s strategies, technologies, and processes supporting the product are effective in their current form and will lead to the retention of those activities that have contributed to the product’s success (Grohsjean et al. 2012). As a result, managers are more likely to keep products on the market longer.

That product termination decreases as performance falls below the aspiration level reflects the idea that failure triggers problemistic search: “search that is stimulated by a problem… and is directed toward finding a solution to that problem” (Cyert and March 1963, p. 121). The firm’s specific problem-solving approach will depend on how far product performance falls below the aspiration level. Such is the prediction of behavioral theories that posit that managers utilize multiple reference points in decision making (Blettner et al. 2014). In particular, March and Shapira (1992) offer a shifting focus model, which assumes that managers may focus on either an aspiration or on survival, depending on the performance shortfall’s severity. The basis for this model is their observation that managers see aspirations and survival as distinct from each other and that sufficient decreases in performance may be interpreted as a step closer to the depletion of solutions (Forlani 2002, Boyle and Shapira 2012). Under such conditions, managerial attention shifts to a survival threshold and away from the aspiration level, and corresponding actions are redirected to efforts to avoid the “threat” of complete failure (Staw et al. 1981).

In the context of this study, the shifting focus model would predict that as product performance falls below aspiration levels, managers will continue to invest in existing products and culling will slow, but as the performance-aspiration gap gets sufficiently large, culling will accelerate. This implies a U-shaped relationship between performance below aspirations and rate of phaseout. Small performance shortfalls will be viewed as reparable discrepancies (Lehman et al. 2011), and solutions will be sought in the proximity of problem symptoms (Cyert and March 1963). Hence, managers will become more willing to leave the (failing) product on the market longer and to risk resources to bolster sales of the product (Bromiley and Wiseman 1989). However, when product performance falls far enough below the aspiration level, attention shifts away from aspirations, and managers may become concerned with the exhaustion of solutions to save the product (March and Simon 1958). They may become increasingly concerned with devoting limited resources to a failure (Kacperczyk et al. 2015) and with making highly visible errors such as failure to cull clearly inferior products (Shapira 1993). As a result, the rate of phaseout then increases. In all, these considerations lead us to propose the following hypotheses.

**Hypothesis 1A (H1A). As the performance–aspiration gap (above aspirations) increases, the rate of product phaseout decreases.**
be served by any particular phaseout decision (Cyert and March 1963). For example, Nokia’s decentralized handset business was beset with a decision making environment of managers trying to reach agreement. Product management at Nokia was described as “stymied by too many people wanting a say in strategic decisions” (Parker and Ward 2010). Under such circumstances, centralized structures may avoid what would be otherwise time-consuming negotiations to resolve discordant preferences on which products to terminate (and which products to launch as replacements). Senior managers have less need to devote excessive effort and time to documenting decisions or justifying thought processes (Isenberg 1986) and can prevent delays stemming from conflict between product managers (Baum and Wally 2003). For example, under Sanjay Jha, Motorola centralized product decisions and alleviated the internecine competition between product teams (Hansell 2009).

Moreover, centralization’s emphasis on vertical information flow may reduce delays owing to coordination problems (Khandwalla 1973), following termination decisions. An emphasis on vertical communication may limit the potentially dense lateral communication flows that would be otherwise required to coordinate among phaseout activities (Galbraith 1977). Executives within a centralized organization have access to information on the complete spectrum of products, which helps them avoid coordination failures and delays associated with poor synchronization of activities (Puranam et al. 2012). This is consistent with research that shows modularization in certain decision-making environments is costly (Birkinshaw et al. 2002) and may sacrifice speed and efficiency for other outcomes (Eisenhardt 1989). Although centralized structures have the potential to burden top managers with decision overload, we argue here, as others (Rivkin and Siggelkow 2003) have, that these factors are outweighed by political and coordination factors. We therefore offer the following:

**HYPOTHESIS 2 (H2). Greater centralization of decision making increases the rate of product phaseout.**

**Centralization and Performance Feedback**

Information processing is only one mechanism through which organization structure may affect termination decisions. Organizational structure also governs the attention focus of managers and, correspondingly, their assessment of performance and response to feedback. The idea that structure shapes attention serves as the foundation for the attention-based view of the firm (Ocasio 1997, Ocasio and Joseph 2005, Bouquet and Birkinshaw 2008, Rerup 2009), and it provides a means to understand why responses to performance feedback may vary with the degree of centralization. From an attention-based perspective, the role of organizational structure in adaptation is to shape the noticing, interpreting, and focusing of time and effort by organizational decision makers on problems and solutions (Ocasio 1997, p. 189). Within complex organizations, the distribution of attention is not uniform, and the relevance of particular elements of the internal and external environment varies according to the structural position of decision makers (Gaba and Joseph 2013). Here we posit that centralization conditions the effects of performance feedback on termination decisions. In particular, we argue that the degree of centralization affects how feedback is interpreted and how responses to performance problems are chosen and enacted.

In decentralized decision-making structures, individual product sales are attended to closely by (lower-level) product managers, who are guided by rules, incentives, and cognitive frames oriented toward meeting unit performance targets. Their identities, interests, and careers are tied more closely to specific products, and hence these managers are likely to focus on the life-cycle management of those products. Moreover, the performance of any one product is likely to accord with team performance evaluations, in which case performance assessment becomes as much a team evaluation as a product performance evaluation (March and Simon 1958). Product performance that falls below aspirations directs attention to the problem product and may reflect negatively on the product team. When phaseout decisions remain low in the hierarchy, this outcome will activate efforts to address the performance problem and to preserve the team’s positive image (Jordan and Audia 2012). Even as product performance declines, decision makers within decentralized structures are likely to exhibit upward bias in their beliefs about the viability of their products—a bias that might cause retention of those products (Audia and Brion 2007).

Within a centralized structure, in contrast, product evaluations are elevated to higher levels in the firm. Retention–termination decisions are vested with more senior-level managers, who focus their attention on the firm’s entirety of products and not just one or two of them. For centralized decision makers, the performance of any one product is less critical to assessments of their own performance. When a product’s performance declines, belief in the attractiveness of other products may be relatively more favorable. As a result, they will be more willing to cull products when performance is poor.

Because the subsequent problemistic search processes are typically restricted to familiar and proximate areas (March and Simon 1958), the choice of solutions will also be affected by organizational hierarchy. In other words, what constitutes a “local” solution will vary with the firm’s locus of decision making. In a decentralized structure, lower-level managers are likely to focus on tactical solutions for particular products, such as making
changes to the marketing strategy. In a centralized structure, problem solving is not circumscribed by product boundaries and is likely to reflect centralized decision makers’ focus on and experience with resource allocation across an entire portfolio of products. Here, solutions will be broader in nature (Sigelkow and Rivkin 2005), and most consequentially for phaseout, problems will be addressed by redirecting resources from unsuccessful to successful products. The centralized firm accomplishes this task by increasing the former’s rate of withdrawal and decreasing the latter’s rate of withdrawal. Over time, centralized organizations develop mental models, rules, and routines that reinforce this pattern of retaining high performers and withdrawing low performers (Rerup and Feldman 2011). For example, centralized firms may create planning and budgeting routines that automatically cut discretionary spending and promotional activities for products that do not perform well (Vancil 1978), effectively shortening their life.

In sum, the greater the elevation of decision-making authority within the firm, the greater the overall focus will be on changes to activities that have significance for maintaining the whole enterprise and for ensuring the portfolio’s survival—even at the expense of a particular product. The differences in problemistic search as performed by centralized/decentralized structures suggest our next two hypotheses.

Hypothesis 3A (H3A). When performance increases above aspirations, centralization amplifies the effects of performance feedback on phaseout (decreases rate of phaseout).

Hypothesis 3B (H3B). When performance decreases below aspirations, centralization attenuates the effects of performance feedback on phaseout (increases rate of phaseout).

Methods
Our data sample covers all German-market mobile phones introduced after January 2004 and terminated before December 2009 by the five largest firms. These companies—LG Electronics, Motorola, Nokia, Samsung Electronics, and Sony Ericsson—accounted for nearly two-thirds of all mobile phones launched in the German market during the time period of our study. An advantage to confining our analysis to a single industry and country setting—and to Germany, in particular—allows us to trace precisely which products have been culled and also eliminates concerns arising from aggregate performance measures that disguise heterogeneity across countries. As confirmed by our interviews and an analysis of culling patterns, product phaseout decisions were country-specific decisions, and as Germany is the largest and most advanced European market for devices, we can trace phaseout decisions in this country with confidence. Our mobile phone data come from the GfK retail panel, regarded as the industry benchmark because it gathers retail sales figures at the points of sale and not from manufacturer surveys. Moreover, GfK, is based in Germany, and its data quality is strongest in its home market. To ensure robustness, we cross-checked the GfK data set with data from competing providers (Klingebiel and Joseph 2016). The mobile phone industry is characterized by high rates of new product introductions and technological advances and short product life (4.3 quarters), which ensures that our data capture multiple generations of manufacturers’ product portfolios. Also, the organizational charts of our sample firms are roughly similar. In each major firm, there is a mobile unit head as well as several layers between that head and the product managers. However, some firms decentralize decisions, whereas other firms centralize. Our sample consists only of a few large firms, but the degree of these firms’ centralization varies over time and thereby enables our relying on within-firm variation to identify the hypothesized effects. Data were analyzed by quarter; the result was a total of 3,192 product-quarter observations comprising 461 product exits across 546 devices within the sample. Financial data are from Compustat and quarterly reports. Descriptive statistics and correlations for all variables are in Table 1.

Dependent Variable
The key event for our analysis is phaseout of a product from the German market. A mobile phone qualifies as a distinct product if at least one of its design characteristics differs from those of the firm’s previous products. The precise date of product phaseout is difficult to establish because such dates are seldom known outside the company (de Figueiredo and Kyle 2006). Mobile phone phaseouts are also complicated by retail distribution channels, which purchase handsets from the manufacturers before selling them to end users. We therefore define phaseout as the cessation of product shipments from the handset manufacturer to German retailers, not as the cessation of all retail sales. The data give an indication of manufacturers’ phaseout decisions in the form of a discontinuous fall in monthly sales in Germany, as the manufacturer does not itself give an exact discontinuation date.

All device phaseouts were coded manually by two individuals. Interrater agreement was high: for 94\% of the devices, the coded phaseout dates were within three months of each other. For those devices whose coded phaseout dates were not within three months, the coders jointly revisited the available information and reached a consensus on the phaseout date. Devices already on the market at the beginning of our observation period (left-censored observations) were not coded. For a subsample of devices, we were able to locate data through internal documentation and found these data to be consistent with our manual coding.
**Performance Feedback.** Feedback consists of performance signals derived from one’s own past performance or the performance of peer firms (Greve 1998). These reference points have been classified by empirical studies as, respectively, historical and social aspiration levels. We follow previous research in the context of a product portfolio and focus on historical aspirations (Audia and Greve 2006, Audia and Brion 2007). Our performance measure is based on quarterly sales at the device level because such sales represent a key performance indicator in the industry and are tracked closely by manufacturers, carriers, and analysts.

We employ a formulation similar to those used in other studies on performance feedback (Baum et al. 2005). We define a historical aspiration level for product performance as an exponentially weighted moving average of its past performance. Let $HA_i$ denote the historical aspirations of phone $i$ at time $t$, and let $P_i$ denote the actual performance of phone $i$ at time $t$. Then, historical aspiration is given by $HA_i = \alpha P_{i,t-1} + (1 - \alpha)HA_{i,t-1}$. In the historical aspiration formula, $\alpha$ can be viewed as an adjustment parameter: a lower $\alpha$ corresponds to giving greater weight to performance farther in the past as compared with the weight given to more recent performance.

The value of $\alpha$ was established by searching over all parameter values of $\alpha$ in increments of 0.1 and then using the value that yielded the maximum log-likelihood; this procedure is consistent with that used in previous studies (Baum et al. 2005, Moliterno and Wiersema 2007). The outcome was $\alpha = 0.1$, although our findings are robust to the weighting scheme. The adjustment parameter so determined suggests that aspiration levels are updated slowly, a result found previously for large multinational firms (Mezias et al. 2002).

The performance–aspiration gap was defined as the difference between performance and aspiration level for each of the phones, or the quantity $(P_i - HA_i)$. We implemented a spline function to compare the effects of a performance–aspirations gap above zero ($P_i > HA_i$) and below zero ($P_i < HA_i$). The technique consists of splitting the variable for historical performance relative to aspirations into two separate variables. Performance above aspirations is set equal to zero for all observations in which the performance (at the phone level) of the focal firm is less than its historical aspiration level; when the phone’s performance is above that level, we use the difference between actual performance and the historical aspirations level (divided by 1,000). Thus, (Performance above historic aspirations)$_i = \max[0, P_i - HA_i]$, where $i$ indicates a particular device and $t$ a particular quarter. Performance below historic aspiration is defined symmetrically. In other words, it is set equal to zero when performance is above the aspirations level and equals the performance–aspirations gap when performance falls below that level: (Performance below historic aspirations)$_i = \min[0, P_i - HA_i, 0]$. Because it
Organizational Structure: Centralization and Oversight

Because firms seldom make structural information publicly available, we use multiple sources to map intertemporal changes in structure for the sample firms. We develop two measures intended to assess the nature of decision making in each firm. For the first measure, we used both primary data (manager interviews) and secondary data (organization charts, books, news articles) to assess the degree of (de)centralization in decision making in each firm (similar to Henderson and Cockburn 1994). For the second measure, we draw on the financial economics literature (e.g., Shin and Stulz 1998) and utilize a measure that reflects the extent of corporate oversight of business unit decision making.

Centralization. To create the first measure, two sets of coders (the authors and firm managers with extensive knowledge of product management) rated, on a 5-point Likert scale, the degree of centralization at each firm for each year of our sample. The authors developed their ratings of centralization by conducting an extensive literature search to build an initial understanding of each firm’s decision-making processes. The search covered newspapers and magazines, several business case publishers, and books spanning a decade of discussion about our five focal companies. In total, we consulted more than 200 sources that addressed the product management process, organizational structure, or organizational change. This extensive review enabled us to build case narratives and facilitated our assessing the degree of centralization for each firm-year over the study period.

Using data from the case narratives, we used the following question to motivate our Likert-scale variable of centralization: What is the degree to which product portfolio decisions must be deferred to someone higher up in the organization for approval (1 for decisions never need to be approved at higher levels, 5 for every decision must be deferred to someone higher up in the organization)? Prior studies of centralization (e.g., Bunderson 2003) document strong consistency across centralization measures constructed from multiple survey questions, which suggests that a single measure is sufficient for an accurate assessment of the construct. An example of high centralization (5) is Samsung in 2006. At the time, Ki Tae Lee was the head of the mobile device unit at Samsung and was seen as responsible for the initial successes in the department following a difficult entry into the mobile device market (Chang 2011). A former Samsung product manager describes his role as follows: “During his period as a head of the mobile device business unit, he controlled everything, including design.” Alternatively, Nokia exhibited a low degree of centralization (2) in the early years of the sample. Proposals were often screened by interlocking management committees, who evaluated projects using consensual rules for decision making (O’Brien 2010).

We then conducted semistructured interviews with individuals in each firm knowledgeable about the product management process. In all cases, we utilized professional or alumni contacts from the authors’ institutions to gain entry into the firms and, from that point, located three middle- to senior-level managers who were familiar with the intricacies of product management by virtue of playing that role themselves or of interacting extensively with the organization’s portfolio management teams. The interviews were approximately an hour in length and transcribed; they were held in person whenever possible. In total, we conducted interviews with 15 managers across the five firms. To ground our data in time, we focus on key facts and events (e.g., Eisenhardt 1989); these include the portfolio management process, the steps in assessing launch and phase-out possibilities, the organizational structure and locus of portfolio management decisions, and changes to the structure during our study period.

Next, we created a formal survey and sent it to our primary senior interview subject from each firm. This survey incorporated the same initial question driving our own assessment and asked potential respondents to evaluate structure for each firm-year starting in 2004. For the Korean companies, we had the survey translated into Korean and then translated back (by another individual) into English to ensure that our questions retained their original meaning. The respondents’ evaluations were then compared with those of the authors.
The interrater agreement was 92%, and there was only one firm for which respondents differed from our own analysis. In that case, we returned to our contacts for a better understanding of the organizational structure and to arrive at a measure that was in line with their own.

Our structure variable exhibited substantial variation over time: the mean of our centralization variable was 3.15, and it ranged from 2 to 5. This range is consistent with firms attempting to reap the benefits associated with flexibility and efficiency during a turbulent stage of industry development (Siggelkow and Levinthal 2005). For example, Bartlett and Ghoshal (1990, p. 305) noted that Ericsson had created a “constant ebb and flow in the centralization and decentralization of various responsibilities.”

Oversight. To ensure the reliability of our centralization measure, we used archival data to construct a second measure that examines the degree of corporate oversight of business unit decisions. For this measure, we considered the extent to which resources were disproportionately allocated by the corporate office to the mobile device unit and, accordingly, the amount of attention paid by the corporate office to their decisions. Linkage between corporate resource allocation and organizational attention has been observed in different contexts (Gilbert 2005), and corporate allocations of resources have been found to predict managerial attention to particular business units (Bouquet and Birkinshaw 2008, Gaba and Joseph 2013). Building upon this foundation, we reason that a disproportionate over- or under-investment in the mobile devices unit by the corporate office would be accompanied by a concomitant degree of oversight of business unit decisions, including those related to products.

To construct our oversight measure, we first calculated an estimate of what capital investment in the mobile devices unit should be in light of observed sales, cash flow of the mobile unit (and of other firm units), and the mobile unit’s external investment opportunities. This expected capital investment was calculated following the approach of Shin and Stulz (1998), whereby we estimated

\[
\frac{I_{\text{mobile},j,t}}{V_{j,t-1}} = a + b \frac{S_{\text{mobile},j,t-1} - S_{\text{mobile},j,t-2}}{S_{\text{mobile},j,t-2}} + c \frac{C_{\text{mobile},j,t}}{V_{j,t-1}} + d \frac{C_{\text{other},j,t}}{V_{j,t-1}} + e q_{\text{mobile},j,t-1} + e_{\text{mobile},j,t},
\]

where \( I_{\text{mobile},j,t} \) represents the firm’s investment in the mobile device segment of firm \( j \) during year \( t \), which we measure as the change in total assets from time \( t - 1 \) to time \( t \); this measure was used because direct capital expenditures were not available at the segment level across all firm years. The term \( V_{j,t} \) is the book value of firm \( j \)'s assets at the end of year \( t - 1 \), and \( S_{\text{mobile},j,t-1} \) denotes sales of firm \( j \)'s mobile device segment during year \( t - 1 \). The term \( C_{\text{mobile},j,t} \) represents the cash flow of firm \( j \)'s mobile device segment during year \( t \), and \( C_{\text{other},j,t} \) represents the cash flow of firm \( j \)'s other segments (i.e., all those except for the mobile device segment) during year \( t \). We used operating profit by segment as our proxy for cash flow because detailed cash information was not available at the segment level. Finally, \( q_{\text{mobile},j,t} \) is Tobin’s \( Q \) for firm \( j \)'s mobile device segment at the end of year \( t - 1 \); it represents investment opportunity in mobile devices. We calculated Tobin’s \( Q \) for mobile devices by using the ratio of firm market value to asset value exhibited by such nondiversified firms as Blackberry and Palm.

We are interested in the degree to which more senior managers are disproportionately more or less involved in the decisions of the mobile device segment, so we constructed a residual measure using the predicted value of \( I_{\text{mobile},j,t}/V_{j,t-1} \) minus the actual observed investment in each year for each firm. A residual that deviates significantly from zero is indicative of a firm’s abnormal (high or low) investment in the mobile phone business unit. A positive residual value suggests that the corporate office has allocated extra capital to the mobile device segment and hence that decisions regarding the segment are more likely to require approval by senior management. Thus, a larger positive value of this residual measure is consistent with a greater degree of oversight, and consequently more involvement of senior managers in decisions such as product phaseout. By similar logic, less involvement of senior managers in these decisions is suggested by a negative residual value. The mean of our residual measure was −0.27, and it ranged from −4 to 1. This wide range is consistent with our measure of centralization. Moreover, the two measures exhibit a correlation of 0.46, which suggests these measures are at least partially capturing similar aspects of centralized decision making.

Other Controls
A variety of controls were included to test for alternative mechanisms that could affect phaseout. Product replacement is an important part of product portfolio management. For our purposes, a direct replacement is one that is launched within two quarters of its predecessor device’s exit and whose launch price is within 10% of that previous device’s launch price. Our definition is consistent with pricing patterns observed in the industry, where marketers tend to “tier” phone offerings into price bands. Our results were robust to alternative formulations of this variable in which the window between exit and launch was compressed to one quarter and the price band was doubled to 20%. We used total firm sales as a proxy for firm size, which may have an indirect influence on the firm’s decision to cull a device
(Henderson and Stern 2004). To account for the information processing benefits associated with the size of the corporate office, we control for absorbed slack; this is defined as the ratio of corporate selling, general, and administrative expenses to sales. We include a measure of focal firm product launches, which we develop by counting all phone launches that occur during the focal quarter at the focal firm to account for interdependencies between product launch plans and product exit plans and resource constraints that are finite within the firm. Several variables specific to the technological characteristics of market participants’ portfolios were also used to control for heterogeneity with respect to the number of 3G phones and number of smartphones in a firm’s portfolio; this enabled us to capture broad improvement in underlying technologies (Greenstein and Wade 1998, de Figueiredo and Kyle 2006). We used a firm’s average portfolio age in each quarter to capture the degree of portfolio obsolescence.

Previous studies (e.g., Henderson and Stern 2004) have employed unit counts over time to approximate experiential learning in a product-culling environment. We take an analogous approach when measuring capability development over time and use the cumulative phone launches by the focal firm since 1997 (the earliest data was available) as a metric for experience. We also included measures of culling experience, calculated as the ratio of total products removed from the market (starting in 1997) to the total number of products introduced up through and including the focal quarter, similar to Sorenson (2000). For each firm, we also developed a composite measure that captures its extent of vertical integration (de Figueiredo and Teece 1996). For each period, we constructed a vertical integration score by summing the number of units within the firm along the industry value chain: semiconductor, network, media/software, and LCD; thus, the maximum score on this measure is 4. We controlled for two industry-level factors, market density (total number of competitors’ devices on the market) and the number of same-period competitors’ phone launches (count of the number of device launches competitors perform in each period) (Sorenson 2000), to account for additional period-specific market dynamics that may affect culling decisions. All time-varying controls were lagged three periods for consistency with our lag structure.

**Empirical Specification**

To examine the factors that affect product phaseout, we applied a piecewise exponential hazard rate model (e.g., Sørensen and Stuart 2000). This model accounts for right censoring (recall that left-censored observations were dropped from our sample), and it offers flexibility in handling not only time-invariant covariates but also time-varying covariates, including our lagged independent variables (Henderson and Stern 2004). Whereas the

![Figure 1](https://example.com/figure1.png)

**Figure 1 Kaplan–Meier Survival Graph (Each Discontinuity Is One Quarter)**

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; we can thus control for any heterogeneity in decision-making processes that is driven by age-dependent factors. The clock in this model is device age, and the individual device is our unit of analysis. We remark that this formulation explicitly accounts for time on the market, which allowed us to model different base hazard rates as the device ages and reflect managerial beliefs that hazard is generally increasing over time. The estimated coefficients can be viewed as generating multipliers of the appropriate underlying base hazard rate, which increases as the mobile device ages. In the piecewise analysis, the pieces consist of 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 1) indicates that the hazard rate differs for each of these time periods, so the intervals we used led to significant improvements in model fit.

Our specification follows that given in Blossfeld et al. (2007), and we assume a constant hazard rate \( r(t) = a \) for each interval of device age. The underlying survivor function within a piece is \( G(t) = e^{-at} \); the hazard rate can be expressed as \( a_i = \exp[x_i, \beta] \), which implies different hazard levels for different observations \( x_i \). The model’s beta coefficients are estimated using maximum likelihood techniques. Robust standard errors, clustered by firm, are also reported to account for the nonindependence of the multiple devices for each firm.

**Results**

Table 2 shows the piecewise exponential hazard rate results for quarterly device phaseout. Log-likelihood tests reveal that the inclusion of our theoretical variables yield significant improvements in model fit over the baseline model. In model (1), we find that the presence of a
### Table 2  Piecewise Exponential Hazard Rate Models for Phaseout

<table>
<thead>
<tr>
<th>Model Hypothesis</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phone level—perf. above aspirations</td>
<td>$-0.012^{**}$</td>
<td>$-0.134^{***}$</td>
<td>$-0.034^{***}$</td>
<td>$-3.747^{**}$</td>
<td>$-0.150^{***}$</td>
<td>$-4.222^{**}$</td>
<td>$-0.175^{**}$</td>
<td>$0.002$</td>
<td>$0.001$</td>
<td>$0.002$</td>
</tr>
<tr>
<td>(P &lt; A)$^2$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Phone level—perf. below aspirations</td>
<td>$0.003^{**}$</td>
<td>$0.813^{***}$</td>
<td>$0.359^{**}$</td>
<td>$0.304^{**}$</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Indicator: In lowest 20% of sales</td>
<td></td>
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<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Centralization</td>
<td>$0.297^*$</td>
<td>$0.385^*$</td>
<td>$0.287^*$</td>
<td>$0.203^*$</td>
<td>$0.325^*$</td>
<td>$0.265^*$</td>
<td>$0.173^*$</td>
<td>$0.009$</td>
<td>$0.009$</td>
<td>$0.009$</td>
</tr>
<tr>
<td>Centralization+P &lt; A</td>
<td>$-0.005^*$</td>
<td>$0.958$</td>
<td>$0.035^{**}$</td>
<td>$1.032$</td>
<td>$0.038^{***}$</td>
<td>$0.009$</td>
<td>$0.009$</td>
<td>$0.009$</td>
<td>$0.009$</td>
<td>$0.009$</td>
</tr>
<tr>
<td>Centralization+P &gt; A</td>
<td>$-0.024$</td>
<td>$-0.022$</td>
<td>$0.171^{***}$</td>
<td>$0.089^*$</td>
<td>$0.043$</td>
<td>$0.043$</td>
<td>$0.043$</td>
<td>$0.043$</td>
<td>$0.043$</td>
<td>$0.043$</td>
</tr>
<tr>
<td>Device controls</td>
<td>Indicator: Replacement</td>
<td>$0.354^{**}$</td>
<td>$0.615^*$</td>
<td>$0.356$</td>
<td>$0.166$</td>
<td>$0.517$</td>
<td>$0.662^*$</td>
<td>$0.512$</td>
<td>$0.280$</td>
<td>$0.666^*$</td>
</tr>
<tr>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: $^{*}$ $p < 0.1$, $^{**} p < 0.05$, $^{***} p < 0.01$
<table>
<thead>
<tr>
<th>Model</th>
<th>Hypothesis</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>H1A</td>
<td>H1B</td>
<td>H1B</td>
<td>(sur)</td>
<td>H2</td>
<td>H3A</td>
<td>H3B</td>
<td>H3B</td>
<td>Full</td>
<td>Full</td>
</tr>
</tbody>
</table>

| Firm controls |
|---------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
|               | Firm size       | −0.000***       | −0.000***       | −0.000***       | −0.000***       | −0.000***       | −0.000***       | −0.000***       | −0.000***       | −0.000***       | −0.000***       |
|               |                 | (0.000)         | (0.000)         | (0.000)         | (0.000)         | (0.000)         | (0.000)         | (0.000)         | (0.000)         | (0.000)         | (0.000)         |
|               | Absorbed slack  | 2.901*          | 2.547*          | 3.259***        | 2.310*          | 2.846*          | 2.623           | 3.249***        | 1.931           | 3.252*          | 2.107           |
|               |                 | (1.231)         | (1.496)         | (1.187)         | (1.007)         | (1.455)         | (1.830)         | (1.311)         | (1.292)         | (1.503)         | (1.746)         |
|               | # of focal firm | 0.059***        | 0.056***        | 0.063***        | 0.053***        | 0.058***        | 0.057*          | 0.064***        | 0.047**         | 0.066**         | 0.050*          |
|               | launches in period | (0.011) | (0.021) | (0.010) | (0.013) | (0.012) | (0.023) | (0.010) | (0.015) | (0.020) | (0.023) |
|               | # of 3G phones  | 0.039           | 0.043           | −0.035          | 0.226           | −0.103          | −0.021          | −0.284          | 0.217           | −0.293          | 0.153           |
|               | in portfolio    | (0.219)         | (0.340)         | (0.189)         | (0.209)         | (0.212)         | (0.338)         | (0.195)         | (0.213)         | (0.323)         | (0.312)         |
|               | # of smartphones| −0.312          | −0.325          | −0.219          | −0.523*         | −0.195          | −0.301          | 0.050           | −0.577*         | 0.071           | −0.501          |
|               | Average portfolio age | −0.096 | −0.049 | −0.069 | −0.113 | 0.058 | 0.067 | 0.094 | 0.045 | 0.109 | 0.064 |
| Industry controls |
|               | # of competitors’ phones on market | −0.008*** | −0.008*** | −0.007*** | −0.008*** | −0.008*** | −0.008*** | −0.008*** | −0.009*** | −0.008*** | −0.009*** |
|               |                 | (0.002)         | (0.002)         | (0.002)         | (0.002)         | (0.002)         | (0.002)         | (0.002)         | (0.003)         | (0.003)         | (0.003)         |
|               | # of competitors’ launches | 0.014*** | 0.016** | 0.012** | 0.016** | 0.017** | 0.015** | 0.016** | 0.016** | 0.016** | 0.016** |
|               |                 | (0.004)         | (0.006)         | (0.004)         | (0.005)         | (0.005)         | (0.006)         | (0.005)         | (0.006)         | (0.006)         | (0.005)         |
|               | Log-likelihood  | −169.958        | −132.161        | −168.567        | −143.283        | −166.102        | −126.100        | −161.889        | −135.016        | −119.007        | −112.512        |

Note: All time-variant covariates are lagged by three quarters. Standard errors are displayed in parentheses.

*p < 0.10; **p < 0.05; ***p < 0.01; ****p < 0.001.
replacement device is associated with higher rates of product turnover. This effect becomes significant when performance above aspirations is included in the specification. We find a significant inverse relation between firm size and rate of product culling (p < 0.001). Large firms may have additional resources and so are better able to leave products on the market longer (Bromiley 1991). Absorbed slack has a positive effect on termination decisions, which suggests there are some information processing advantages of large corporate office.4

We find that the launch of new devices within focal period increases the hazard for any particular device; this is consistent with the logic that the firm will not want to cannibalize its new devices (which are sold for higher prices) with devices at the end of their life cycle. Our technology/feature variables (3G and smartphones) increased and reduced hazard in our controls only model, respectively, but neither variable was significant. They remain largely insignificant across all specifications. These two key technological developments were in relatively early stages in our sample, and it is not yet clear that the industry had yet fully adjusted to these technologies in terms of product phaseout processes.

We find no relationship between average portfolio age and culling. We find a marginally significant negative effect (p < 0.10) relating cumulative phone launches to phaseout. Contrary to results reported in Sorenson (2000) and in Henderson and Stern (2004), the coefficient for our degree of culling experience variable is not significant; in other words, current culling rates seem largely unrelated to previous rates in the same market. Note that the average product life (4.3 mean quarters of product time on market) was much shorter in our study than in those by Sorenson (2000), who examined workstations (2.84 mean years of product time on market), and Henderson and Stern (2004), who examined personal computers (2.31 mean years). In line with de Figueiredo and Teece (1996), we find that vertical integration in upstream product development capability has a significant impact on the firm’s downstream exit rates; this follows because such firms can more effectively navigate interdependencies in product development and manufacturing. We find that the number of competitors’ launches increases the likelihood of culling, while the number of competitors’ phones on the market lowers the likelihood that a product is culled. These results are consistent with our qualitative interviews, which suggested that managers actively engage in scanning the competitive landscape and evaluating the performance of competing devices and may adjust product phaseout timing to coincide with competitor moves.

Model (2) shows how phone-level feedback affects phaseout when performance is above aspirations. Consistent with H1A, we find that performance above aspirations is associated with a decreasing hazard of product phaseout at the p < 0.01 level. This finding accords with our argument that product managers maintain the status quo when performance is above aspirations. For models (3) and (4), which show the squared term and survival-level indicator approaches to test H1B, we find that the linear term is significant and negative at the p < 0.001 level, suggesting that managers engage in local search for solutions when performance falls moderately below aspirations. Furthermore, the squared term in model (3) is positive and significant (p < 0.001) just as the survival-level indicator variable is positive and significant in model (4) (p < 0.001). These findings indicate that when performance falls sufficiently below aspirations, attention shifts to survival, the exhaustion of solutions, and phaseout. We note the better fit of the survival-level indicator variable approach, consistent with prior studies (Miller and Chen 2004, Boyle and Shapiro 2012) that use a discrete cutoff for survival.

Model (5) tests H2 and examines the effect of centralization measure on phaseout. Consistent with H2, we find a statistically significant coefficient for centralization in model (5) (p < 0.05); the main effect coefficient is positive across all specifications, suggesting that the coordination properties of centralized structures facilitate phaseout behavior.

Models (6)–(8) show how centralization conditions the effects of performance feedback on phaseout. Model (6) shows the interaction of performance above aspirations and centralization. Model (7) shows the interaction of both performance below aspirations and performance below aspirations squared with centralization. Model (8) replaces the squared term and its interaction with the survival-level indicator variable and its interaction. We emphasize that the “main effect” of feedback cannot be interpreted as simply the coefficient for the phone-level feedback variable (Jaccard and Turrisi 2003) because the coefficient for the main effect represents its influence when the other term in the interaction is zero. Yet in our sample the zero value is meaningless: it does not occur because centralization is measured on a 1 to 5 scale.5 Accordingly, the formal test for H3A is whether the centralization-performance feedback interaction variable in model (6) is significant and negative. We find support for H3A (p < 0.05); centralization reduces the likelihood of culling when performance is above aspirations. In model (7), which examines the squared term interaction, we lose significance on the main effect of performance below aspirations as well as the squared term and respective interaction terms. In model (8), which uses the survival-level indicator variable to identify devices below the survival threshold, we find support for H3B, as the interaction terms between the centralization variable and our performance below aspirations and survival-level indicator variables are positive and significant at p < 0.01 and p < 0.001 levels, respectively. Again, we find the survival-level indicator approach is a better representation of our data.
Our full models (models (9) and (10)) generally retain both sign and significance from their respective constituent models. We note that the significance of the survival-level indicator and interaction variable is slightly weakened (though still statistically significant) in model (10) compared to model (8). As noted above, the survival-level indicator approach remains a better fit to our data than the squared term approach. Consequently, we use this model to graph our key findings in Figure 2. The x-axis of Figure 2 corresponds to performance relative to aspirations and the y-axis to the probability that a median device will survive four quarters. The graph plots two lines representing different values of centralization (2 and 4), which illustrate how centralization affects the likelihood of phaseout after four quarters at different levels of performance relative to aspirations. All displayed values are within the data range.

Figure 2 makes an important point by demonstrating that product phaseout depends on the firm’s degree of centralization. The net effect of centralization can either increase or decrease the hazard of phaseout, which suggests a critical link between the behavioral mechanism of performance feedback and the structure of a firm’s decision making. The coefficient for the interaction between performance above aspirations and centralization is statistically significant in model (10) \((p < 0.05)\), and the rate of change of phaseout for an organization with a high degree of centralization is striking. As performance increases above aspirations, a 13-percentage-point difference in the likelihood of retaining a product between organizations with high and low centralization decreases to a 2-percentage-point difference at the 75th percentile of performance above aspirations. Consistent with H3B, we find that decentralized organizations react quite differently to negative feedback than do centralized organizations. As performance becomes worse relative to aspirations, the difference in culling between centralized and decentralized organizations increases by an additional 29 percentage points, suggesting that more centralized firms (centralization = 4) are 1.99 times more likely to cull products performing below aspirations than more decentralized firms (centralization = 2) through four quarters.

**Robustness**

Models (11)–(14), which are included in Table 3, test the robustness of our findings. These models build on the survival-level indicator approach used in model (10), which was the best fitting model. Model (11) replicates model (10) while removing from the sample all devices that were also launched in the United States, South Korea, or the United Kingdom. This allowed us to account for any influence of large markets (e.g., United States, United Kingdom, South Korea), and in the case of the United States and Korea, the home markets for three of our five firms. For both measures of centralization, we identified less than a third of devices as being strictly German (which leaves us with 1,053 product-quarters, comprising 151 product exits across 191 devices). Even so, all of our hypotheses remain supported in this German-only sample.

To account for organizational and temporal idiosyncrasies that may broadly affect phaseout patterns, we incorporate both firm and year dummy variables as an additional sensitivity analysis. Model (12) shows the results of adding firm and year dummies to model (10). When these dummies are included in the regression, the results are similar to those reported in model (10).\(^6\) We note reduced significance on our survival-level indicator variable \((p < 0.10)\). Note that incorporating firm and year dummies does not improve the model’s statistical fit at the 5% level of significance (i.e., a log-likelihood test comparing the fit of model (10) versus

---

**Figure 2** (Color online) The Effect on Product Phaseout of Centralization and of Performance Relative to Aspirations.

<table>
<thead>
<tr>
<th>Cen. = 2</th>
<th>75th Pctle</th>
<th>P(device culled through 4Q)</th>
</tr>
</thead>
<tbody>
<tr>
<td>46%</td>
<td>74%</td>
<td>63%</td>
</tr>
<tr>
<td>Cen. = 4</td>
<td>92%</td>
<td>91%</td>
</tr>
</tbody>
</table>

Note. Dashed and solid plots indicate where centralization equals 2 and 4, respectively. These results correspond to Table 2, Model (10). Cen., Centralization.
### Table 3 Robustness Tests of Piecewise Exponential Hazard Rate Models for Phaseout

<table>
<thead>
<tr>
<th>Model</th>
<th>(11) German only</th>
<th>(12) Fixed effects</th>
<th>(13) Oversight (as centralization)</th>
<th>(14) Oversight (as control)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phone level—perf. above aspirations</td>
<td>0.010 (0.007)</td>
<td>0.002 (0.002)</td>
<td>-0.012* (0.006)</td>
<td>-0.012* (0.006)</td>
</tr>
<tr>
<td>Phone level—perf. below aspirations</td>
<td>-1.820** (0.956)</td>
<td>-0.170*** (0.038)</td>
<td>-0.046*** (0.009)</td>
<td>-0.046*** (0.008)</td>
</tr>
<tr>
<td>Indicator: In lowest 20% of sales</td>
<td>1.432** (0.510)</td>
<td>0.290* (0.160)</td>
<td>0.508 (0.311)</td>
<td>0.527* (0.304)</td>
</tr>
<tr>
<td>Centralization</td>
<td>0.462*** (0.088)</td>
<td>0.287* (0.157)</td>
<td>1.156 (0.123)</td>
<td>0.200 (0.096)</td>
</tr>
<tr>
<td>Centralization * P &gt; A</td>
<td>-0.010*** (0.003)</td>
<td>-0.004* (0.002)</td>
<td>0.000 (0.001)</td>
<td>0.142*** (0.010)</td>
</tr>
<tr>
<td>Centralization * P &lt; A</td>
<td>0.441** (0.151)</td>
<td>0.037*** (0.008)</td>
<td>0.193*** (0.013)</td>
<td>0.105* (0.042)</td>
</tr>
<tr>
<td>Centralization * Indicator: In lowest 20% of sales</td>
<td>0.319* (0.134)</td>
<td>0.091* (0.045)</td>
<td>0.014 (0.061)</td>
<td>0.134 (0.218)</td>
</tr>
<tr>
<td>Device controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Indicator: Replacement</td>
<td>0.567 (0.702)</td>
<td>0.340 (0.363)</td>
<td>-0.331 (0.217)</td>
<td>-0.349 (0.218)</td>
</tr>
<tr>
<td>Firm controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Firm size</td>
<td>-0.000** (0.000)</td>
<td>-0.000*** (0.000)</td>
<td>-0.000*** (0.000)</td>
<td>-0.000*** (0.000)</td>
</tr>
<tr>
<td>Absorbed slack</td>
<td>6.415*** (1.166)</td>
<td>3.003 (1.971)</td>
<td>4.886*** (1.116)</td>
<td>3.614** (1.329)</td>
</tr>
<tr>
<td># of focal firm launches in period</td>
<td>0.110** (0.035)</td>
<td>0.031* (0.015)</td>
<td>0.067* (0.039)</td>
<td>0.063 (0.039)</td>
</tr>
<tr>
<td># of 3G phones in portfolio</td>
<td>-1.364** (0.425)</td>
<td>0.613*** (0.087)</td>
<td>-0.207 (0.421)</td>
<td>0.137 (0.328)</td>
</tr>
<tr>
<td># of smartphones in portfolio</td>
<td>-1.466** (0.492)</td>
<td>-1.006*** (0.141)</td>
<td>-0.247 (0.507)</td>
<td>-0.445 (0.392)</td>
</tr>
<tr>
<td>Average portfolio age</td>
<td>0.407 (0.308)</td>
<td>0.083 (0.205)</td>
<td>0.072 (0.204)</td>
<td>0.000 (0.176)</td>
</tr>
<tr>
<td>Cumulative phone launches</td>
<td>-0.086*** (0.025)</td>
<td>0.002 (0.004)</td>
<td>-0.024 (0.019)</td>
<td>-0.015 (0.015)</td>
</tr>
<tr>
<td>Experience: Degree of culling</td>
<td>-0.076 (0.235)</td>
<td>0.175 (0.306)</td>
<td>0.407 (0.274)</td>
<td>0.344 (0.287)</td>
</tr>
<tr>
<td>Vertical integration</td>
<td>-1.629* (0.854)</td>
<td>3.303*** (0.423)</td>
<td>1.928* (0.893)</td>
<td>2.320*** (0.684)</td>
</tr>
<tr>
<td>Industry controls</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td># of competitors’ phones on market</td>
<td>0.013 (0.012)</td>
<td>-0.012*** (0.003)</td>
<td>-0.003 (0.003)</td>
<td>-0.004* (0.002)</td>
</tr>
<tr>
<td># of competitors’ launches</td>
<td>0.013*** (0.003)</td>
<td>0.015* (0.007)</td>
<td>0.016* (0.005)</td>
<td>0.015* (0.006)</td>
</tr>
<tr>
<td>Firm dummies</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Year dummies</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>N</td>
<td>1.053 (6.819)</td>
<td>3.192 (110.596)</td>
<td>2.123 (47.257)</td>
<td>2.123 (47.014)</td>
</tr>
</tbody>
</table>

Note. All time-variant covariates are lagged by three quarters. Standard errors are displayed in parentheses. 
* p < 0.10; ** p < 0.05; *** p < 0.01; **** p < 0.001.

that of model (12) is not significant at the p < 0.05 level. It is therefore reasonable to conclude that a model excluding these parameters yields a statistically similar and thus adequate fit to the data.

Models (13) and (14) explore the robustness of our findings to our measure of oversight in decision making. Because segment-level data were not available for all firms for all the years used to construct this measure,
our observations dropped to 2,123 product-quarters comprising 322 product exits across 418 devices. A t-test between these samples found that the phones in each sample did not differ significantly (at the $p < 0.05$ level) with regard to either sales or price, indicating that both samples contain generally similar devices. In model (13), which uses the oversight variable in lieu of organizational measure, we generally find a pattern of sign and significance similar to that in model (10). In model (14), which uses the oversight variable as an additional control for centralization (centered to account for possible collinearity), we again report findings consistent with model (10), though the interaction term between centralization and performance above aspirations loses significance at the $p < 0.05$ level.

Finally, our ability to interpret the estimated coefficients on structure as representing causal effects hinges on the extent to which centralization is exogenous. While it is indeed plausible that a poorly performing firm may centralize (thus making centralization endogenous to performance), it is much less likely that a single poorly performing product would drive firms of this size to centralize their structure and corresponding routines, communication channels, and informal interactions. Interviews with industry executives indicate that because the portfolio management process is highly routinized (e.g., firms introduce an average of 4.37 phones and cull 4.24 phones per quarter), the degree of centralization does not vary across products. To assess potential endogeneity more directly, we reran our analysis removing extreme blockbuster and failure products (which might otherwise garner more top management attention) and found no difference in results. We then regressed the degree of centralization from 2004 through 2009 on the rate of product culling and firm performance (measured by sales) during the same time period, finding no relationship between these performance measures and degree of centralization. We repeated this analysis using our measure of oversight, again finding no relationship. Overall, we conclude that endogeneity of structure is unlikely driving our results.

Discussion and Conclusion

This study develops a model to explain the effects of organizational structure and performance feedback on termination decisions. In particular, we examined the effects of centralized and decentralized decision-making structures on product phaseout in the mobile device industry. Much of the behavioral theory research implicitly assumes that performance feedback induces uniform responses irrespective of the firm’s decision-making structure. However, we reasoned that this may not be the case because structure shapes not only information processing, but also attention to problems and solutions. We argued first that, owing to consolidated authority and vertical communication patterns, firms with centralized structures demonstrate decision making and coordination patterns that, ceteris paribus, increase the rate of phaseout. Second, we argued that perceptions of problems and solutions vary across the vertical hierarchy—as do the corresponding responses to feedback. Centralized structures focus managerial attention on all products, and when addressing performance problems, they initiate strategic actions that affect the entire portfolio. Rather than make tactical changes to each product, centralized decision makers shift resources from lower- to higher-performing products and cull the poor performers more quickly.

Our study makes several contributions. First, we offer new insights into the determinants of product phaseout and termination decisions more broadly. Termination and its inverse (retention) have long been of interest to economists, psychologists, and organizational scholars. The phenomena of termination, abandonment, and exit have been linked to a variety of population-level (Hannan and Freeman 1984), industry-level (Greve 1995), organizational-level (Mitchell 1994, Guler 2007, Shimizu 2007, Klingebiel 2012, Gaba and Dokko 2015), and individual-level (Staw et al. 1981) drivers. We augment this body of work by highlighting the joint contribution of structure and behavioral factors and, in particular, the nature of feedback within corporate hierarchies. For example, we do find some evidence consistent with the escalation of commitment to a course of action (Staw et al. 1981, Guler 2007). Studies show that people tend to commit more resources to the activity that caused the loss to justify the prior commitment. Yet our findings and data do not fully reflect escalation behavior. Our results suggest that centralized structures exhibit less escalation behavior than decentralized structures, even as performance decreases. This finding runs counter to extant research (e.g., Gilbert 2005) characterizing management as unduly rigid, and suggests the idiosyncratic attention paid to problems and alternatives plays a role in the commitment to a prior course of action.

Second, this study augments the growing scholarship on performance feedback by considering important conditional effects imposed by structure. The role of organizational structure has been largely absent in studies of performance feedback, and the results of this study argue for more research linking cognitive and structural explanations of adaptive behavior. Our results make clear that forces reducing the rate of phaseout are not dispersed uniformly throughout the firm; in other words, the spatial and temporal conjunction of certain players and types of feedback are consequential. A corresponding yet broader contribution of this paper is to link key pillars of the Carnegie school: hierarchy and aspirations. For the most part, these pillars have been developed independently; the result is a wealth of theory for each that is largely
As a third contribution, our focus on centralization expands the scope of theory concerning organization design and builds on the classic and contemporary research in this field (Burton and Obel 2004). We document in particular that the role of organizational structure in decision making involves more than information processing, and we highlight the effect of structure on situated attention (Ocasio 1997)—what we call situated selection. The logic of situated selection is distinct from traditional information processing views (Galbraith 1974, Tushman and Nadler 1978). In the latter, the problem for decision makers is one of matching information processing capacity to the level of environmental complexity. From the situated selection perspective, however, the problem facing decision makers is one of identifying which problems and solutions they should consider. In this view, then, information is not uniformly processed, but instead is attended to and responded to idiosyncratically, contingent on the vertical location of the decision maker in the hierarchy. In the context of situated selection, choice is guided by the locus of decision making and local interactions, rather than by universal structural or strategic controls or the external environment. Managerial decisions, contingent on the attention-directing qualities of the structure, determine whether individual strategies, products and technologies are retained or eliminated.

Our research joins a growing number of recent studies that show design choices affecting organizational outcomes (e.g., Christensen and Knudsen 2010, Cardinal et al. 2011, Boumgarden et al. 2012, Karim and Kaul 2015), yet it focuses specifically on the attentional implications of structure (see Rhee et al. 2014, Sengul and Obloj 2014). Our findings are also consistent with studies which show that hierarchies are more conservative in allocating resources to products (Christensen and Knudsen 2010, Csaszar 2012). For example, research shows that centralized structures often require that resource allocation decisions need to be validated by successive ranks of the hierarchy, and as a result are likely to grant fewer resources to product maintenance (or any product). Although we are agnostic as to the particular screening behavior of the firm, it would clearly amplify our findings regarding centralization.

As Figure 2 illustrates, high levels of decentralization may alter the interpretation of performance below aspirations (and hence the response to that performance) differently than do high levels of centralization. Although research has demonstrated that the interpretation of information becomes more distorted under greater centralization (Sutcliffe 1994), a decentralized structure creates specialized attention channels and so provides fewer global signals to those making decisions (Puranam et al. 2006, Csaszar 2012). Our model of centralized feedback may be the most suitable—at mean levels of performance—if rapid phaseout is desired or required. It is worth noting that Apple, when lead by Steve Jobs, was quite successful with centralized decision making. However, the business model of Apple differed greatly from that of large manufacturers (e.g., Nokia and Samsung) and led to relatively few product introductions, simplifying the corresponding phaseout process. So even though our study has clear implications for the decision process across many of these areas, more work is needed if we are to understand better the performance implications of linking feedback and particular structures.

An obvious limitation of this study is that our data cover a particular and limited period in the mobile device industry. This period was one of great turbulence and technological change, as 3G technology was still nascent and a dominant design had yet to emerge. The first iPhone was launched near the end of our sample period, during which network externalities provided by the Android and iOS operating systems had not been developed. Another limitation is that the global mobile device industry had relatively few large players. Although we were able to exploit intrafirm variation in decision-making structure, future research might usefully investigate whether the level of decision making accounts for meaningful variance in smaller firms, too. Likewise, the degree of interdependencies in phase-out activities across firms was largely the same, which suggests an opportunity for future studies to examine the degree of interdependencies in decision making as a boundary condition. Finally, caution should be exercised when generalizing our findings to other industries. The scope of what constitutes a “new” product in this industry may differ from what is considered a new product in other industries. For example, most new products in the mobile device industry reflect incremental changes to predecessors rather than architectural or radical shifts. Future research could examine the effects of structure on product portfolio decisions across a greater variety of product categories.

Given the renewed interest in corporate-level effects on performance and the increased attention being devoted to organizational architecture (Gulati et al. 2012), it seems that the fields of strategy and organization theory are ready for more studies on the role of attention in complex firms. This paper is an early step in that direction. Although we are beginning to see other work in this vein (e.g., Gavetti 2005, Rerup 2009, Csaszar and Eggers 2013), more research is needed to illuminate the
interconnectedness of cognition, structure, and performance within complex organizations. Our study at least partially substantiates the claim that because structure can affect attention, sense making, and decision making, it is fertile ground for future studies and provides a platform on which other researchers may build.

Acknowledgments
The authors thank Rich Bettis, Phil Bromiley, Rich Burton, John DeFigueiredo, Vibha Gaba, Metin Sengul, William Ocasio, Sim Sitkin, Margerethe Wiersema, Zur Shapira, and three anonymous reviewers for their helpful comments on previous versions of this paper. Seminar participants at Duke University, Manchester University, University of California Irvine, University of California Riverside, Wharton School of Business, Yonsei University, the 2015 Academy of Management meeting, the 2014 Strategic Management Society meeting, the 2013 Transatlantic Doctoral Consortium, and the 2013 Utah-BYU Winter Strategy Conference also provided constructive input.

Endnotes
1Less is known about how managers form reference groups (Greve 1998); hence, defining the social group relevant to comparable products would prove extremely difficult in the mobile phone industry, where devices compete—with respect to technology, features, and prices—not only within a given product generation but also across generations.
2An alternative specification is to utilize a dummy variable that takes a value of 1 when performance is above aspirations (Bromiley and Harris 2014). Inclusion of the dummy term in the model allows for a discontinuity at the point where performance is equal to aspirations. Results from this alternative specification do not differ from our approach and are available from the authors.
3Our findings are not sensitive to changes (e.g., 10%, 15%) in the chosen threshold.
4Prior literature (Gaba and Joseph 2013) has found a relationship between corporate-level and business-unit-level performance feedback and the launch of new products. While we find an impact of product launch on phaseout, we find no significant effects of corporate- and business-unit-level feedback on product phaseout.
5In model (6), for example, performance feedback above aspirations slows phaseout at all values of centralization (with an implied coefficient of \(-0.008[0.002+2\ast-0.005]\) at a centralization of 2 and \(-0.023[0.002+5\ast-0.005]\) at a centralization of 5). Consequently, the effects of performance feedback above aspirations in models (6), (9), and (10) all demonstrate a similar effect (with differing magnitudes depending on the degree of centralization) as in model (2), which shows the main effect of performance feedback above aspirations only.
6Our results are also robust to the inclusion of either firm or year dummies separately.
7Problem solving in the face of limited information and escalating commitment both differ also from structural inertia, a third possible explanation for the observed behavior. However, it is unlikely that inertia explains our findings. Phaseout is a central part of the portfolio management process, and procedures are in place to ensure that it occurs within a reasonable period of time following a sales decline. Both lower- and upper-level managers are capable enough to cull products, and neither should be disadvantaged in terms of the structures or routines that allow them to do so. Our empirical results bear this expectation out, since the conventional wisdom is that the senior management levels are characterized by greater behavioral inertia, or less adaptive behavior (Tripsas and Gavetti 2000). In contrast, we find that centralized structures always exhibit faster culling.

References


**Joseph, Klingebiel, and Wilson: Organizational Structure and Performance Feedback**

**Organization Science, Articles in Advance**

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